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Review article

Standalone DC microgrids: Planning, operation and uncertainty management

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ABSTRACT

Standalone power systems in remote areas have traditionally relied on continuously operating fossil fuel generators, leading to high operational costs, reduced efficiency, and substantial carbon emissions. Standalone direct current (DC) microgrids have emerged as a promising alternative due to their lower conversion losses, improved integration of renewable energy sources (RES), and enhanced compatibility with modern DC-native loads and storage technologies. Despite these advantages, the planning, operation, and uncertainty management of standalone DC microgrids remain technically challenging. Intermittent RES generation, stochastic load behaviour, lack of mature standards, and complex control requirements introduce significant design and operational challenges. While numerous studies have proposed methods to address issues in sizing, optimisation, control, energy management, and uncertainty management, a comprehensive and structured review that connects these aspects across the full lifecycle of DC microgrid development is still lacking. This article addresses this gap by providing a systematic review of the state-of-the-art in planning methodologies, operational strategies, and uncertainty management techniques for standalone DC microgrids. The review synthesises theoretical frameworks and practical implementations, critically evaluates existing approaches by identifying their strengths and limitations, and highlights the interdependencies among planning, real-time operation, and uncertainty mitigation. Finally, the article outlines key research challenges and future opportunities to support the reliable, cost-effective, and sustainable deployment of standalone DC microgrids. The novelty of this study lies in its integrated perspective spanning planning, operational control, and uncertainty management, offering valuable guidance for researchers, system designers, and practitioners.

Abbreviations: AC, Alternating Current; AFLC, Adaptive Fuzzy Logic Control; AI, Artificial intelligence; ANN, Artificial Neural Network; BESS, Battery Energy Storage System; CFI, Carbon Free Island; CHO, Cheetah Optimisation; CPLEX, Complex Linear Programming Expert; DC, Direct Current; DER, Distributed Energy Resources; DG, Distributed Generation; DLR, Dynamic Line rating; DOD, Depth of Discharge; DRL, Deep Reinforcement Learning; DSM, Demand Side Management; EENS, Expected Energy Not Supplied; ELF, Equivalent Loss Factor; ELV, Extra Low Voltage; EMS, Energy Management Systems; ENS, Energy Not Supplied; ESS, Energy Storage Systems; EV, Electric Vehicle; FL, Fuzzy Logic; FRE, Fraction of Renewable Energy; GHG, Green House Gas; HOMER, Hybrid Optimisation Model for Multiple Energy Resources; HPP, Hydro Power Plant; IBD, Interlinking Bidirectional DC/DC Converter; IDBO, Improved Dung Beetle Optimisation; IEC, International Electrotechnical Commission; IEEE, Institute of Electrical and Electronics Engineers; IRR, Internal Rate of Return; LADRC, Linear Active Disturbance Rejection Control; LCOE, Levelized Cost of Electricity; LED, Light Emitting Diode; LOLE, Loss of Load Expectation; LOLP, Loss of Load Probability; LPSP, Loss of Power Supply Probability; LSTM, Long Short-Term Memory; LV, Low Voltage; MAE, Mean Absolute Error; MAPE, Mean Absolute Percentage Error; MILP, Mixed Integer Linear Programming; ML, Machine Learning; MPC, Model Predictive Control; MPPT, Maximum Power Point Tracking; MV, Medium Voltage; NPV, Net Present value; NREL, National Renewable Energy Laboratory; NSGA-II, Non-dominated Sorting Genetic Algorithm II; NSRDB, National Solar Radiation Database; ORC, Organic Rankine Cycle; P2P, Peer to Peer; PCA, Principal Component Analysis; PPO, Proximal Policy Optimisation; PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses; PSO, Particle Swarm Optimisation; PUCF, Per unit Carbon Footprint; PV, Photovoltaic; PVGIS, Photovoltaic Geographical Information System; REC, Renewable Energy Curtailment; RES, Renewable Energy Sources; RII, Renewable Intermittency Index; RMSE, Root Mean Squared Error; SAIDI, System Average Interruption Duration Index; SAIFI, System Average Interruption Frequency Index; SDP, Semi Definite Programming; SOC, State of Charge; SPL, System Performance Level; THD, Total harmonic Distortion; V2G, Vehicle to Grid

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1. Introduction

As global efforts to mitigate climate change intensify, the transition from fossil fuel-based electricity generation to renewable energy sources (RES) has emerged as a cornerstone of sustainable development. In 2024, RES accounted for over 32% of global electricity generation, as depicted in Fig. 1, underscoring a strong international commitment to decarbonisation [1]. This shift is particularly critical for remote and off-grid regions, such as offshore oil and gas platforms, mining camps, rural communities, small islands, and isolated research stations, that typically rely on standalone power systems [2]. Traditionally powered by fossil fuel generators, these systems face high operating costs, substantial greenhouse gas (GHG) emissions, and logistical challenges related to fuel transport and storage, prompting increased scrutiny and a push toward cleaner and more efficient alternatives [3].

Renewable energy offers a cleaner and more sustainable alternative. However, its inherent intermittency introduces challenges to integration. To ensure reliability and system stability, energy storage systems (ESS) and intelligent energy management systems (EMS) are critical [4]. Addressing these challenges requires technological innovation, the development of supportive policies and regulatory frameworks, and active public engagement [5]. A microgrid is a localised energy system capable of operating either in conjunction with the main grid or independently, designed to integrate these RES with ESS and loads. Its primary function is to enhance energy reliability, resilience, and sustainability by balancing generation and demand within a defined boundary [6]. Traditionally, microgrids were built around alternating current (AC) architectures to align with existing grid infrastructure. However, the increasing penetration of direct current (DC)-based RES like solar photovoltaic (PV), along with DC-compatible ESS and loads, has prompted a shift toward DC microgrids [7]. DC microgrids provide several advantages, including the elimination of conversion losses, improved overall system efficiency, reduced capital and operational costs by minimising the need for transformers and AC-DC/ DC-AC converters, and enhanced compatibility with modern DC loads such as electronic devices, light-emitting diode lighting, and electric vehicles (EVs) [8]. Therefore, implementing DC microgrids in standalone power systems can significantly enhance efficiency, facilitate the integration of diverse RES, and support system scalability.

1.1. Standalone DC microgrids: context and key considerations

Powering standalone systems through DC microgrids presents notable challenges in planning, implementation, and operation. Planning studies for standalone DC microgrids typically aim to achieve 4 key objectives: 1) Minimising electricity generation costs, 2) Reducing carbon emissions to the lowest feasible level, 3) Ensuring reliable and high-quality power supply for end-users, and 4) Delivering a safe and uninterrupted electricity supply that consistently meets user demand [9]. These objectives are often addressed through optimisation studies that utilise historical weather data, such as solar irradiance and wind speed, to determine cost-effective and reliable configurations, based on the relative prioritisation of each objective [10].

Sizing of standalone DC microgrids is generally conducted over a long-term planning horizon, often spanning 25 years, to incorporate both technical and economic considerations. These include interest rates, equipment degradation, and projected changes in operational and replacement costs [11]. A range of optimisation methodologies has been applied in the planning of standalone DC microgrids, from statistical estimation techniques to advanced approaches such as ANNs [12]. Software tools like the hybrid optimisation model for multiple energy resources (HOMER) are widely used to automate the optimisation process [13]. However, further customisation is often necessary to accommodate specific sets of objectives and constraints. Additionally, the integration of emerging flexible loads, such as EVs, EV charging stations, and hydrogen production facilities, introduces further complexity into the planning process [14]. These evolving demands underscore the need for more sophisticated implementation strategies and dynamic planning frameworks.

Standalone DC microgrids, due to their small scale and high penetration of RES, are particularly vulnerable to fluctuations in power generation. These fluctuations can cause significant variations in DC bus voltage, necessitating the deployment of robust control strategies to regulate the DC link voltage and coordinate the operation of multiple converter units under both transient and steady-state conditions [15]. Early implementations relied on decentralised control strategies, where local controllers operated equipment based solely on locally measured parameters. While these approaches are resilient and straightforward, their limited access to system-wide voltage and current data reduces effectiveness, particularly during rapid power fluctuations [16]. To overcome these limitations, advanced decentralised techniques have been developed, including adaptive droop control [17], power sharing algorithms [18], and sliding mode control [19]. However, the absence of communication links in purely decentralised systems restricts real-time coordination, often resulting in suboptimal voltage regulation and power-sharing accuracy [20].

Centralised control strategies, by contrast, utilise comprehensive system-wide information to compute optimal control actions. These methods offer superior performance in voltage regulation and operational coordination but are associated with high computational requirements, potential single points of failure, and increased implementation costs [21]. To balance the strengths and limitations of both approaches, distributed control topologies have emerged. These frameworks enable localised decision-making while incorporating limited communication among controllers, thereby enhancing scalability, resilience, and partial coordination without the infrastructure demands of fully centralised systems [22]. Further improvements are achieved through hierarchical control architectures, which organise control functions into multiple levels [23]. Primary control ensures fast local voltage and current stability; secondary control restores system parameters to nominal values and enhances power-sharing; and tertiary control optimises energy flow and economic dispatch across the system [24]. This layered approach supports real-time responsiveness, efficient energy management, and flexible system expansion, making hierarchical control particularly well-suited for complex and dynamic standalone DC microgrid environments.

These control strategies in standalone DC microgrids are typically embedded within the EMS, which coordinates the operation of generation sources, ESS, and electrical loads [25]. The EMS plays a pivotal role in maintaining system equilibrium, optimising operational performance, and ensuring overall reliability [26]. It integrates functionalities such as energy and demand forecasting, control algorithms, and demand-side management, integrated with optimisation techniques to schedule and manage generation assets, ESS, and loads in both day-

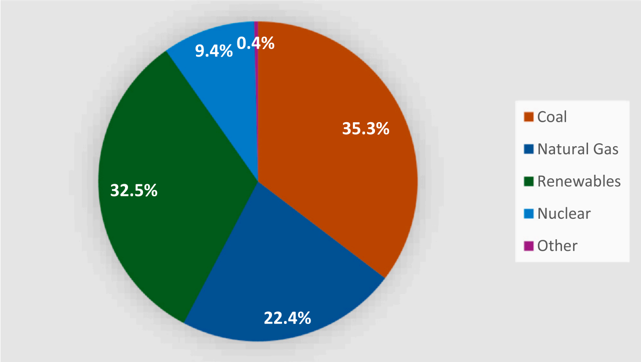


Fig. 1. Global electricity generation mix – 2024.
Data Source: [1].

ahead and real-time scenarios [27]. Moreover, uncertainty modelling approaches such as probabilistic methods and robust optimisation are increasingly being incorporated into EMS frameworks [28]. These techniques enable the analysis and quantification of uncertainties associated with renewable energy generation and fluctuating demand, thereby enhancing the reliability and resilience of standalone DC microgrid operations under dynamic and unpredictable conditions [29].

1.2. Research gaps and motivation for a comprehensive review

Numerous review articles in the literature examine the various challenges associated with DC microgrids operating in both grid-connected and islanded modes. Robust control strategies for DC microgrids were systematically explored in Jin et al. [8], emphasising their advantages over AC systems in terms of stability, flexibility, and simplicity. It contributes by detailing the operational frameworks in both grid-connected and islanded modes, analysing design aspects and stability challenges, and presenting representative solutions to guide the transition toward more flexible DC microgrid implementations. The challenges and strategies for integrating RES into industrial microgrids, while maintaining reliability and minimising costs and emissions, have been explored in Polleux et al. [9]. It contributes by offering a cross-disciplinary analysis, from fossil engine dynamics to control theory, highlighting the limitations of conventional mitigation methods, identifying key reliability constraints in industrial DC microgrids, and proposing applicable control strategies, with oil and gas microgrids as a central case study. The planning and protection aspects of DC microgrids, which are becoming increasingly relevant due to the rise in DC loads and the integration of RES, have been discussed in [30]. It contributes by analysing the interdependence of planning and protection strategies, documenting their strengths and weaknesses, and proposing improvements in reliable DC microgrid design.

A comprehensive review of the challenges and control strategies for integrating renewable energy into DC microgrids was presented in Alam et al. [21], emphasising issues such as voltage regulation, energy management, and uncertainty. Its key contribution lies in systematically evaluating existing methodologies, identifying research gaps, and offering targeted recommendations to enhance RES integration and guide future developments in DC microgrid control. In Al-Ismail [31], 15 years of research on DC microgrid planning, operation, and control were consolidated, detailing various control strategies and coordination methods for secure and efficient power sharing across grid-connected and islanded systems, while documenting the advantages and limitations of existing approaches. The authors in Al-Ismail [32] thoroughly analyse existing voltage control and power management strategies in DC microgrids, including centralised, decentralised, distributed, and advanced control techniques, by documenting their benefits and limitations across grid-connected and islanded configurations to support stable and reliable microgrid operation. A comprehensive overview of low and medium-voltage DC microgrids is presented in Fotopoulou et al. [33], detailing their advantages over AC systems, integration with the AC grid, topologies, control strategies, applications, ancillary services, and standardisation challenges, with a focus on their practical implementation and current limitations.

The current state of DC microgrids was explored in Jithin et al. [34] by examining their architectures, protection schemes, power quality, inertia, communication systems, and economic operation, while comparing configurations and showcasing real-world projects to highlight practical advancements and challenges. The DC microgrid architecture, control structures, and EMS were investigated in Ali et al. [35], offering a focused analysis of various EMS strategies and optimisation techniques, particularly for residential applications, to enhance the secure, reliable, and cost-effective use of distributed energy resources (DERs). The control strategies, power converter topologies, and energy management approaches for hybrid ESS in DC microgrids were discussed in Kowsalya [36], emphasising the role of artificial intelligence (AI) techniques, such as fuzzy logic, neural networks, and reinforcement learning, in addressing the complexities of both standalone and grid-connected configurations. A summary of the contributions from the mentioned review articles on DC microgrids is presented in Table 1.

Although several review articles have examined DC microgrids recently, as summarised in Table 1, only a limited number have explicitly focused on standalone DC microgrids. Unlike grid-connected systems, standalone DC microgrids operate independently of the main grid and rely solely on local generation and storage resources. As a result, their planning and operation must prioritise the efficient utilisation, coordination, and storage of locally generated energy. These unique constraints necessitate a dedicated review to assess the current state of research and outline future directions.

Existing reviews typically address either planning or operation in isolation, without providing an integrated perspective. A holistic analysis is essential to capture the full research landscape, particularly because standalone DC microgrids are often deployed in remote or harsh environments characterised by limited data availability, variable operating conditions, and heightened reliability requirements. Under such circumstances, managing uncertainty becomes a critical challenge. However, the literature lacks a systematic review of uncertainty management approaches tailored specifically to standalone DC microgrids.

This manuscript addresses these gaps by presenting a comprehensive review of planning, operational strategies, and uncertainty management techniques for standalone DC microgrids. It highlights their potential as sustainable solutions for isolated power systems and synthesises key methodologies for design, control, and energy management. Furthermore, it examines uncertainty management approaches applicable to both planning and operational phases, offering insights into methods capable of improving system robustness and performance.

Table 1
Coverage of the contributions of recent review articles on DC microgrids

Review manuscript	Year	Coverage of contributions in challenges of DC microgrids				
		Planning	Energy management	Control	Uncertainty management	Focus on standalone systems
[8]	2022	✗	✗	✓	✗	✗
[9]	2022	✗	✓	✗	✗	✓
[30]	2023	✓	✗	✗	✗	✗
[21]	2024	✗	✓	✓	✓	✗
[31]	2021	✓	✗	✓	✗	✗
[32]	2024	✗	✓	✓	✗	✗
[33]	2021	✗	✗	✓	✗	✗
[34]	2023	✗	✗	✗	✓	✗
[35]	2021	✗	✓	✗	✗	✗
[36]	2024	✗	✓	✓	✗	✗
This study		✓	✓	✓	✓	✓

DC = direct current.

Finally, the manuscript outlines future research directions aimed at enhancing existing methodologies and mitigating the impact of uncertainty. These contributions provide valuable guidance for researchers and practitioners seeking to advance the development, optimisation, and reliable operation of standalone DC microgrids.

This manuscript is organised as follows. Section 2 presents the methodology used to select articles from literature databases for the review. Section 3 provides an overview of standalone DC microgrids, including their key components. Section 4 highlights the potential of the DC microgrids to deliver both economic savings and environmental benefits when implemented in standalone power systems. Section 5 reviews the planning methodologies commonly adopted for standalone DC microgrids. Section 6 presents a comprehensive discussion of various control algorithms and EMS strategies developed for these applications. Section 7 addresses the challenges posed by uncertainties in RES and load demand, as well as the techniques employed to mitigate these issues. Section 8 outlines future research directions identified through this review. Finally, Section 9 concludes the manuscript by summarising the key insights and contributions.

2. Review methodology

To address the research questions and achieve the objectives of this review, relevant literature on the challenges and opportunities associated with standalone DC microgrids was systematically identified. A structured review process consistent with the preferred reporting items for systematic reviews and meta-analyses guidelines [37] was employed to ensure rigorous screening and selection of the most pertinent studies. An initial keyword-based search was conducted in the Scopus database, selected for its extensive coverage of high-quality journals and recent publications—focusing on the period 2021–2025 [38]. Boolean queries such as (“standalone” OR “islanded” OR “isolated”) AND (“DC microgrid” OR “direct current microgrid”) were applied, with syntax refined for each database as needed. Publications prior to 2021 were also included, although only highly cited studies were retained. A parallel search was carried out using Google Scholar, and the results were cross-checked against those from Scopus. Duplicate entries were removed, and the consolidated dataset served as the foundation for the initial screening phase.

To ensure a focused and high-quality review, a systematic screening methodology was then applied to identify studies most relevant to standalone DC microgrids. Titles, abstracts, and conclusions were reviewed to exclude works with only marginal relevance to core themes such as microgrid control, energy management, uncertainty handling, planning and operation, protection, economic performance, and environmental impact. Full-text assessments were subsequently performed on the shortlisted articles, and studies lacking comprehensive coverage of these areas were excluded. This process resulted in a refined body of literature appropriate for in-depth evaluation.

The final collection of studies enabled the identification of key challenges and emerging opportunities in the integration of RES within standalone DC microgrids. Significant opportunities include the deployment of inertia support mechanisms, optimisation of hybrid energy storage configurations, and improvements in both economic feasibility and environmental sustainability. Fig. 2 presents the methodology used to filter and select the relevant literature. By synthesising insights from the curated set of studies, this review provides a structured and comprehensive overview of the current state of standalone DC microgrids, highlighting existing limitations and potential pathways for future advancement. The findings aim to inform researchers, industry practitioners, and policymakers in shaping effective strategies for the development and deployment of RES-enabled standalone DC microgrid systems.

3. Standalone DC microgrids

A DC microgrid operating independently without support from the utility grid is referred to as a standalone DC microgrid [39]. Its primary components typically include RES such as wind turbines and solar PV systems; fossil fuel-based generators like diesel engines and gas turbines; ESS including batteries, supercapacitors, and hydrogen storage; and various types of electrical loads, as illustrated in Fig. 3. Due to the intermittent nature of renewable energy, which often constitutes a significant portion of the energy mix in standalone DC microgrids, ensuring system stability and reliability presents a substantial challenge [40]. This challenge is further compounded by the inherently low inertia of DC microgrids, which limits their ability to respond effectively to rapid fluctuations in load or generation [41]. Maintaining voltage stability and power balance in such systems relies heavily on fast-acting control mechanisms and responsive ESS technologies. ESS play a critical role in addressing these challenges by providing inertial support through bidirectional energy exchange with the microgrid [42]. High-energy-density storage systems, such as batteries and hydrogen storage, help maintain steady-state operation by supplying or absorbing power as needed. Meanwhile, high power density ESS, such as supercapacitors, are capable of responding rapidly to transient events, including sudden load changes, faults, or abrupt drops in generation, by quickly absorbing or releasing power [43]. Table 2 provides a comparative overview of the main ESS used in standalone DC microgrids, evaluated against key performance factors.

Given the reliability requirements of standalone DC microgrid applications, conventional fossil fuel-based power generation sources, such as diesel generators and gas turbines, are often integrated into the system via AC/DC converters to provide additional support and enhance system stability [47]. However, these fossil fuel-based generators produce high levels of carbon emissions and entail significant operational and maintenance costs, leading to economic and environmental concerns [48]. Therefore, a standalone DC microgrid should be designed to minimise the operation of these conventional energy sources.

The loads in a standalone DC microgrid can be categorised into AC and DC loads. DC loads can be directly connected to the DC bus, while AC loads require inverters for integration. Additionally, loads can be classified as critical or non-critical. Critical loads must always be supplied with power, whereas non-critical loads can be interrupted, curtailed, or rescheduled during generation deficits or periods of high electricity costs [49]. These load management strategies can be implemented through properly designed EMS algorithms. Furthermore, standalone DC microgrids can integrate specialised loads such as EV chargers, hydrogen fuelling stations with on-site hydrogen generation, and vehicle-to-grid systems [50]. The operation of these loads requires advanced EMS algorithms tailored to their specific requirements, ensuring efficient and reliable performance within the microgrid.

3.1. Standards for standalone DC microgrids

Although standalone DC microgrids are experiencing rapid growth, the development of comprehensive implementation standards remains limited. Several organisations are currently working toward establishing standardisation frameworks for DC microgrids, many of which can be adapted for standalone applications [51]. At present, IEEE 2030.10-2021, the IEEE Standard for DC Microgrids for Rural and Remote Electricity Access Applications, is the most widely referenced guideline for standalone DC microgrid design and operation [52]. Related International Electrotechnical Commission (IEC) standards (e.g., IEC 60364–8–2, IEC 62898, and the IEC 62939 series) provide safety, wiring, and protection requirements that can be adapted for DC microgrid applications [53]. Ongoing standardisation efforts are converging toward harmonised low voltage (LV) DC voltage levels, improved DC fault-clearing protocols, and interoperable control interfaces [54].

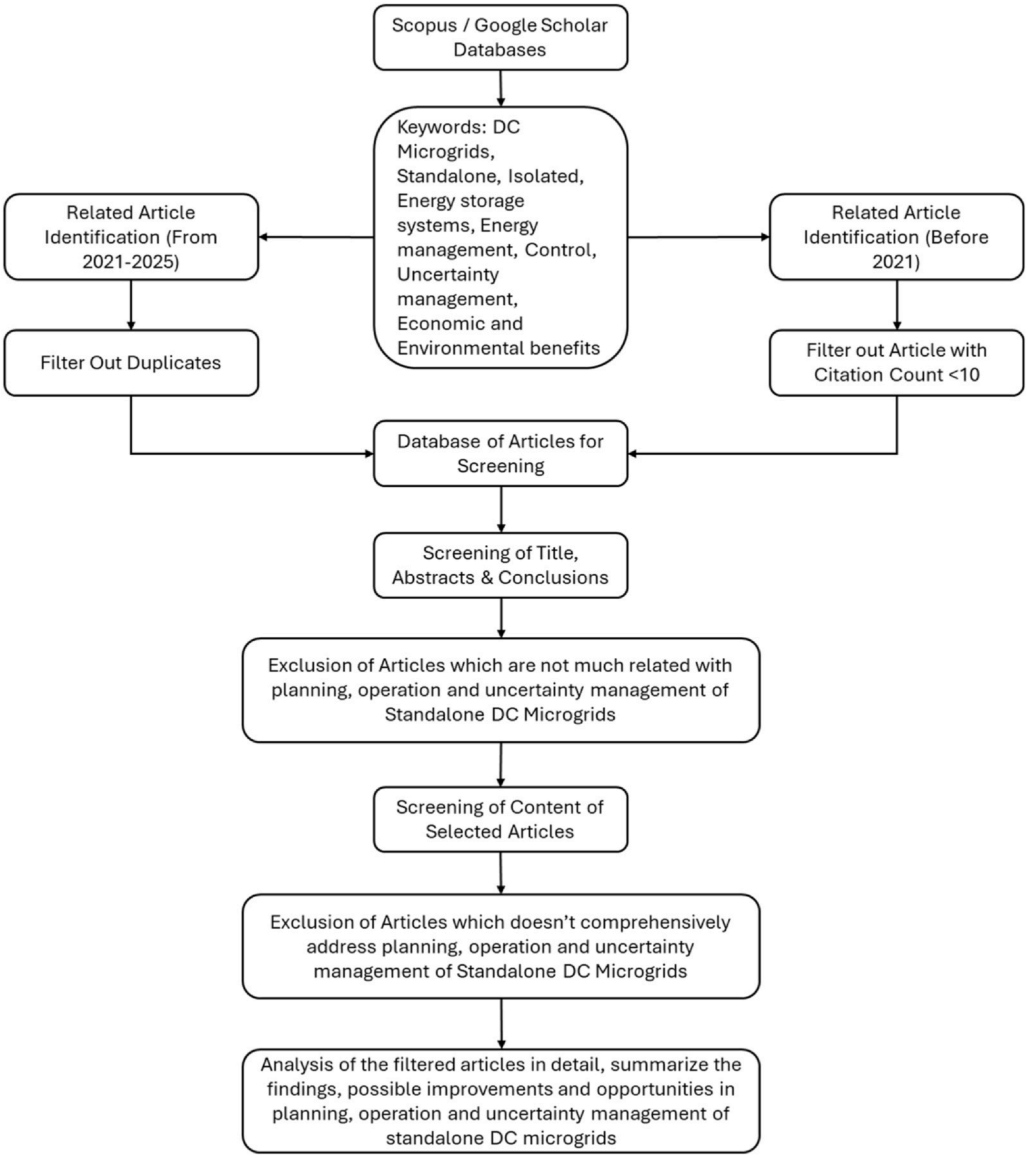


Fig. 2. Flowchart of review methodology. DC = direct current.

Table 3 summarises the commonly adopted DC voltage levels, converter rating ranges, and fault-clearing requirements, all of which are applicable to standalone DC microgrid configurations [55].

The converter rating ranges and DC fault-clearing windows directly influence the protection and control strategies adopted across different voltage classes of standalone DC microgrids. At extra low voltage levels, converter capacities are small, and fault currents are naturally limited by source impedance, making electronic or solid-state protection practical [56]. Control strategies, therefore, emphasise voltage regulation and load-sharing rather than complex protection coordination. In LV systems, higher converter ratings and lower line impedances enable larger and faster-rising fault currents. This requires coordinated protection schemes using fast solid-state or hybrid breakers, with converter controls (e.g., current limiting and soft-start functions) actively supporting fault ride-through and system stability [57]. Medium voltage (MV) DC microgrids, by contrast, involve large-capacity converters whose fault contributions can reach tens of kiloamps within microseconds. Consequently, protection strategies depend heavily on ultra-fast hybrid DC breakers and detailed current-limiting control at the converter level. The narrow fault-clearing window at MV levels also requires tight integration between primary control, secondary control and protection logic to prevent cascading failures [58].

4. Benefits of DC microgrids for standalone power systems

DC microgrids offer several advantages for standalone power systems, which are traditionally powered by fossil fuel-based generators. These conventional generators typically incur higher operational costs due to fuel prices and the associated logistics of fuel transportation. In addition, they contribute significantly to GHG emissions, which adversely impact the environment [36]. In contrast, RES-based standalone DC microgrids provide a cost-effective alternative by utilising clean energy sources such as solar PV and wind power. This not only reduces operational expenses but also significantly lowers GHG emissions, contributing to climate change mitigation [59]. Furthermore, since RES are often located near the point of use, the capital investment for standalone systems is generally lower compared to grid-connected alternatives, as expenses related to power transmission and distribution are minimised [60]. Therefore, the adoption of DC microgrids in standalone applications offers substantial economic and environmental benefits to both users and the wider community. Overall benefits from utilising DC microgrids for standalone power systems are presented in Fig. 4.

An economically viable standalone DC microgrid topology to support a carbon-free island (CFI) is proposed in Mun et al [61], while

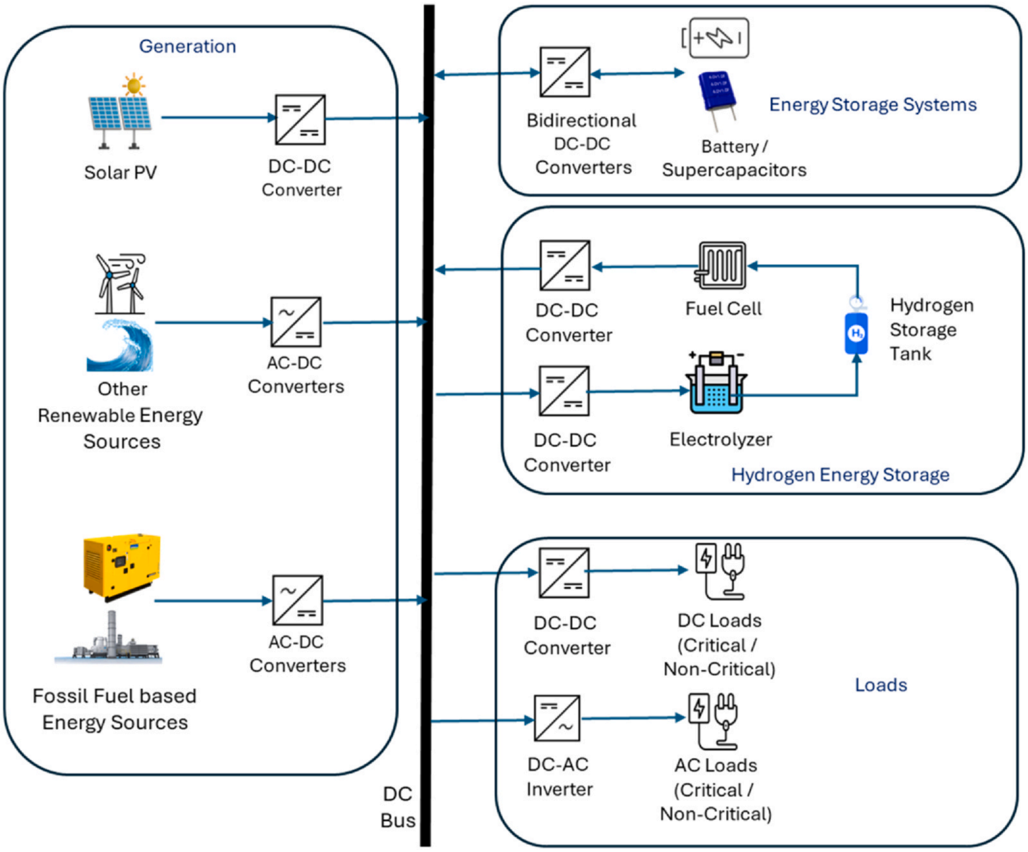


Fig. 3. Architecture of a standalone DC microgrid. AC = alternating current; DC = direct current; PV = photovoltaic.

ensuring acceptable reliability levels. The study analyses various configurations that integrate solar PV, wind, batteries, and fuel cells, evaluates their economic and reliability performance, performs sensitivity analyses, and proposes suitable models aligned with Korea's CFI policy. A carbon-neutral standalone DC microgrid is presented in [62] for campus electrification, incorporating crypto mining devices and second-life batteries to optimise operational costs using a mixed-integer linear programming approach. The results demonstrate significant cost savings, particularly as Bitcoin prices increase, with second-life batteries proving to be more cost-effective than new batteries. The standalone DC microgrid proposed for VIT University in Subramanian et al. [63] delivers notable economic and environmental benefits by minimising total net present cost, energy cost, and CO_2 emissions through optimal system sizing using HOMER Pro. The optimal system configuration, comprising solar PV, fuel cells, batteries, wind turbines, and a diesel generator, achieves zero unmet load at a low cost of 24.91 INR/kWh.

A smart adaptive EMS for sustainable voltage regulation in DC microgrids is proposed in [64], aimed at supporting carbon neutrality while enhancing economic performance by efficiently operating a slow-response small HPP via iterative load estimation and mitigating battery stress using an adjustable energy controller. Comparative analysis and validation through simulations and real-time testing indicate that the proposed adaptive EMS improves voltage stability by 22.7%, increases HPP utilisation by 55.27%, and reduces battery current stress by 98.17%. The development of a decentralised DC microgrid for rural electrification is explored in [65], interconnecting nanogrids, each serving 4–6 households with solar panels and lead-acid batteries, to enhance community energy access and economic resilience. The system design and control algorithm are validated through simulations, laboratory experiments, and field deployment in Madagascar, confirming the technical viability of the swarm electrification concept.

Aiming to enhance PV utilisation and extend battery lifespan to reduce base station operating costs, a hierarchical EMS based on the improved dung beetle optimisation (IDBO) algorithm is proposed in Han et al. [66]. The 3-layer control framework incorporates bus voltage regulation, dynamic power balancing through state of charge (SOC) and virtual resistance, and cost minimisation using IDBO, with simulation results indicating daily cost reductions of 14.64% and 9.49% compared to the baseline. In Alluraiah and Vijayapriya [67], an optimal standalone DC microgrid system is designed by evaluating local renewable energy potential to sustainably meet the energy needs of Doddipalli village in Andhra Pradesh, India. Employing HOMER software for system optimisation, the study integrates hydrogen production and assesses multiple configurations, identifying a PV/Wind/Diesel Generator setup as optimal with a lower levelized cost of electricity (LCOE) of $0.0751/kWh, a high renewable energy fraction of 97.8%, and reduced CO_2 emissions, demonstrating strong economic and environmental performance.

A solar-powered desalination system for Larak Island, Iran, is designed, modelled, and optimised in Kiehbadroudinezhad et al. [68], to achieve low cost, minimal environmental impact, and high reliability using the division algorithm, life cycle assessments via SimaPro show that a 10% loss of power supply probability (LPSP) offers the best trade-off. The inclusion of a diesel generator significantly increases environmental harm, highlighting the benefits of a purely solar-driven system for sustainable freshwater production. In Jayasinghe et al. [69], a novel multi-objective optimisation framework is introduced for sizing equipment, depth of discharge (DOD) of battery energy storage system (BESS), and controllable load sharing in a standalone DC microgrid comprising RES and a backup diesel generator. By employing a genetic algorithm to minimise life cycle cost and carbon emissions, the framework incorporates battery degradation into the cost model. It identifies an optimal DOD range, resulting in notable reductions in LCOE

Table 2
Comparative summary of ESS technologies for standalone DC microgrids referenced from [44–46].

Feature	ESS type				
	Lithium-ion batteries	Redox flow batteries	Thermal energy storage	Supercapacitors	Hydrogen storage (fuel cell + electrolyser)
Energy density	High (150–250 Wh/kg)	Low–medium (20–50 Wh/kg)	Highly variable (depends on medium; typically, low–medium)	Very low (5–10 Wh/kg)	Very high gravimetric; low–medium volumetric
Power density	Medium–high	Medium	Low (unless coupled with ORC or thermoelectric systems)	Very high	Low–medium
Response time	Fast (ms–s)	Moderate (s)	Slow–moderate	Ultra-fast (µs–ms)	Slow–moderate (seconds–minutes)
Cycle life	3000–8000 cycles	> 10,000 cycles	Very high (especially sensible heat thermal ESS)	> 1,000,000 cycles	No “cycles” limit, but components degrade moderately
Efficiency	90–95%	70–85%	Moderate–high (50–90%, depending on system)	> 95%	Low (25–45% round-trip)
Scalability	Modular, but limited by cost and thermal constraints	Excellent; energy and power decoupled	Excellent for large-scale, long-duration storage	Limited—best for short-duration, high-power needs	Excellent—energy scalable via tank size
Cost	Moderate–high	High capital cost	Low– moderate; depending on material and system	High per kWh	High capital; low long-term storage cost
Safety	Requires thermal management	Very safe, non-flammable	Very safe	Very safe	Requires strict hydrogen handling; storage pressure considerations
Application in standalone DC microgrids	Daily cycling, RES smoothing, peak shaving	Long-duration storage, deep cycling	Waste-heat utilisation, industrial microgrids, long-duration thermal buffering	Transient support, fault ride-through, voltage stabilisation	Seasonal storage, long-duration backup, remote/offshore microgrids
Key advantages	High efficiency, compact, mature	Long life, high safety, flexible scaling	Cost-effective for bulk storage; compatible with CHP and hybrid systems	Exceptional power density and response	Suitable for very long-duration storage; supports sector coupling
Key limitations	Thermal runaway risk; aging	Low energy density; auxiliary systems	Low exergy; generally unsuitable for fast response	Cannot store significant energy	Low efficiency; slow response; system complexity

DC = direct current; ESS = energy storage systems; RES = renewable energy sources. CHP = combined heat and power

Table 3

Comparison of standalone DC microgrids with DC voltage levels, converter ranges and fault clearance levels

Category of standalone DC microgrids based on voltage level	DC Voltage level	Converter Rating Range	DC Fault clearance level	Applications
ELV	12 – 48 V	< 5 kW	< 2 kA	Lighting, low-power loads, telecommunications
LV	50 – 400 V	5 – 250 kW	2 – 10 kA	Data centres, EV charging stations, transport applications
MV	600 V – 3 kV	250 kW – 10 MW	10 – 25 kA	Ships, data centres, industrial applications

DC = direct current; ELV = extra low voltage; EV = electric vehicle; LV = low voltage; MV = medium voltage

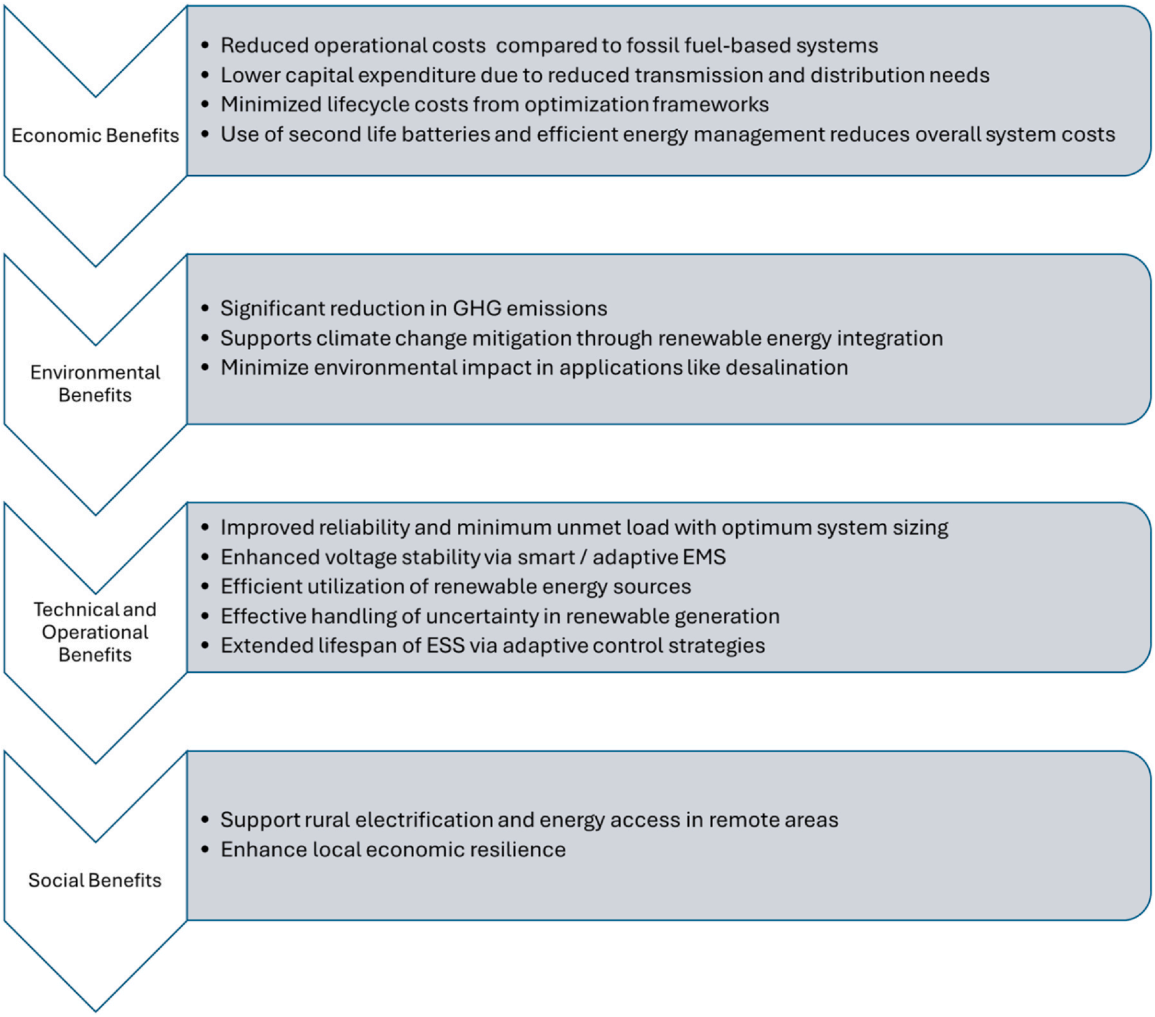
and CO_2 emissions compared to previous approaches. An optimal operational strategy for droop-controlled standalone DC microgrids is presented in [70], balancing small-signal stability with economic and environmental objectives by optimising the principal eigenvalue and other key parameters. The method uses the dragonfly algorithm for tuning droop parameters and integrates uncertainty from PV generation, with simulation results on 6-bus and 3-bus DC microgrid systems validating its adaptability and effectiveness.

5. Planning of standalone DC microgrids

The planning of standalone DC microgrids is a critical process that involves assessing energy demand, evaluating RES, and determining system requirements to ensure optimal performance. Unlike conventional power systems, standalone microgrids operate independently from the primary grid and must be carefully designed to balance energy generation, storage, and consumption [71]. The planning process comprises several key components, including load assessment, meteorological analysis, and system requirement evaluation. These elements collectively inform the development of an optimisation approach for microgrid design. Fig. 5 illustrates the structured planning process for a standalone DC microgrid.

5.1. Load assessment

Accurate load assessment is crucial for designing a reliable and efficient microgrid. The demand profile of a microgrid is influenced by several factors, including base load, peak load, load growth, seasonal variations, and load prioritisation [72]. Base load represents the minimum power requirement, while peak load defines the maximum



- Reduced operational costs compared to fossil fuel-based systems
- Lower capital expenditure due to reduced transmission and distribution needs
- Minimized lifecycle costs from optimization frameworks
- Use of second life batteries and efficient energy management reduces overall system costs

- Significant reduction in GHG emissions
- Supports climate change mitigation through renewable energy integration
- Minimize environmental impact in applications like desalination

- Improved reliability and minimum unmet load with optimum system sizing
- Enhanced voltage stability via smart / adaptive EMS
- Efficient utilization of renewable energy sources
- Effective handling of uncertainty in renewable generation
- Extended lifespan of ESS via adaptive control strategies

- Support rural electrification and energy access in remote areas
- Enhance local economic resilience

Fig. 4. Benefits of DC microgrids in the application of standalone power systems. DC = direct current; ESS = energy storage systems; EMS = energy management systems; GHG = greenhouse gas.

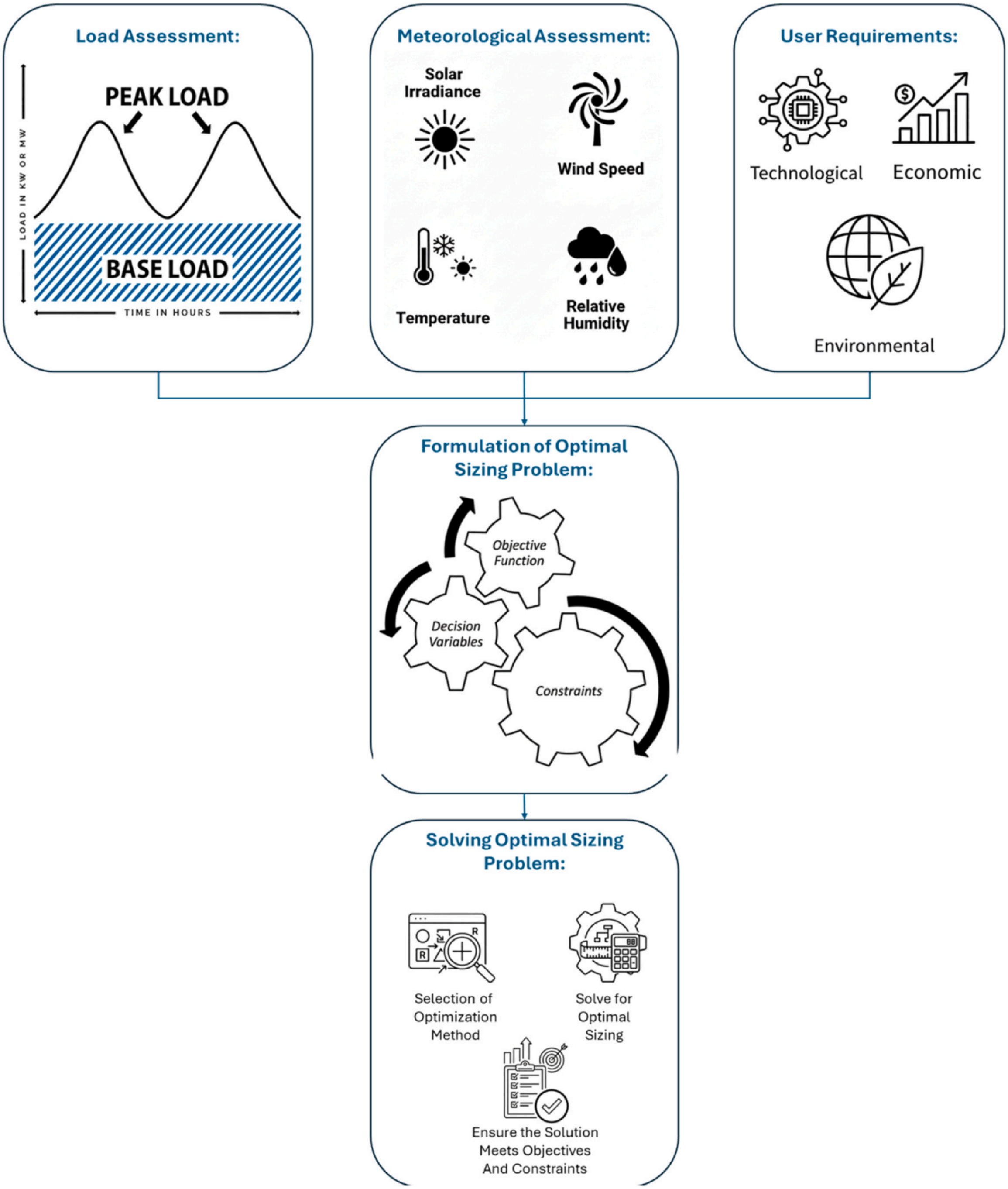


Fig. 5. Planning process of a standalone DC microgrid. DC = direct current.

demand within a given period. Load growth must be considered to accommodate future expansions and increased energy consumption. In Kaur et al. [73], a wind- and PV-based standalone DC microgrid was designed for a telecommunication base station in a remote area, considering future expansions and upgrades to the telecommunication system. Seasonal variations have a significant impact on energy demand, particularly in applications with temperature-sensitive loads. A standalone DC microgrid design based on peer-to-peer (P2P) energy trading between prosumers was proposed in Yu et al. [74], where the total profit and environmental impact varied due to seasonal factors. Specifically, considering seasonal variations, the total profit from P2P energy trading decreased by 10%. Additionally, load prioritisation ensures that critical loads receive an uninterrupted power supply while optimising the utilisation of available resources [75].

In May Alvarez et al. [76], a vector-based microgrid design optimisation method was proposed using a multi-objective optimisation approach to ensure power supply to critical loads. Various load assessment techniques, including statistical forecasting, machine learning (ML) models, and probabilistic approaches, have been explored in the literature. A stochastic optimisation method, known as the modified Gauss quadrature-based point estimation method, was applied in [77] to address uncertainties related to load and generation in an isolated DC microgrid design. In Alavi et al. [78], a distributed forecast-based consensus control strategy for DC microgrids was proposed to balance the SOC levels of ESS. This strategy employs a long short-term memory deep neural network-based load forecasting model. Furthermore, a deep learning-based load forecasting technique was introduced in Mehrzadi et al. [79] to predict the dynamic positioning load for a power management system in a standalone DC microgrid for marine applications.

5.2. Meteorological assessment

The availability of RES plays a crucial role in microgrid planning, making meteorological assessment a key factor. The primary parameters considered in this assessment include solar irradiance, temperature, wind speed, and relative humidity [80]. Solar irradiance data is essential for estimating the energy generation potential of PV systems, with variations influenced by geographical location and weather conditions [81]. Temperature impacts PV efficiency, as excessive heat can reduce power output. Wind speed data is critical for evaluating wind turbine performance and determining appropriate turbine capacity for DC microgrid configurations [82].

In Premadasa et al. [83], a genetic algorithm-based multi-objective optimisation method was used to design a standalone DC microgrid, resulting in the selection of low-cumulative-power-output wind turbines and high-output solar PV modules as the optimal solution, depending on the meteorological parameters of the chosen location. Relative humidity affects energy losses in electrical systems and influences the efficiency of certain ESS technologies. The ESS output in a solar PV-based DC microgrid was analysed in Itagi et al. [84], highlighting its correlation with meteorological conditions. Additionally, depending on the location, other RES such as wave energy, tidal energy, and biomass may also be viable for microgrid applications. In Vicente et al. [85], the benefits of integrating marine energy sources into isolated microgrids on Orkney Island were assessed, considering the inclusion of wave and tidal energy. The results demonstrated various advantages, including reduced installed capacity requirements, minimised ESS needs, overall cost savings, and lower excess generation.

5.3. Assessment of user requirements

A well-planned standalone DC microgrid must satisfy multiple economic, technical, reliability, environmental, and geographical requirements [86]. Across the reviewed literature, a range of economic evaluation models has been employed to assess feasibility, yet these approaches remain highly heterogeneous. The most widely used metrics are the NPV and the LCOE, which underpin lifecycle cost analyses in studies utilising tools such as HOMER Pro [87,88]. Other works incorporate broader financial indicators, including IRR, payback period, and cost–benefit ratios, to evaluate long-term investment performance [89].

Multi-objective optimisation frameworks further embed economic criteria into composite cost functions that account for battery degradation, RES variability, carbon pricing, and operational risk [90]. A whale-optimisation-based strategy in Boonraksa et al. [91] designs a standalone DC microgrid with hybrid energy storage, minimising the system's NPV and storage replacement costs. In parallel, technical requirements emphasise system architecture, component configuration, and adherence to power quality standards. Also, Hemmati and Faraji [92] propose a ring-bus-based standalone DC microgrid designed to mitigate harmonics from nonlinear loads, enhance resilience, and improve voltage stability.

Reliability assessment is a fundamental component of standalone DC microgrid planning, ensuring adequate resilience against equipment failures, load fluctuations, and supply–demand mismatches [93]. The integration of RES and ESS significantly influences these assessments. Converter-interfaced RES units lower and reshape fault currents, weakening the effectiveness of conventional overcurrent protection and introducing uncertainties in fault detection [94]. ESS enhance the operational reliability by offering rapid voltage and power support. However, the behaviour of the bidirectional converters complicates protection coordination and the identification of fault signatures further [95]. Consequently, assessing reliability in converter-dominated standalone DC microgrids requires the use of quantitative metrics that capture supply continuity, load satisfaction, and system adequacy under different operating and fault scenarios. Table 4 summarises the most widely adopted reliability metrics in the literature for planning and evaluating standalone DC microgrids.

The reliability of a standalone DC microgrid was analysed in Kuo et al. [99] using dynamic voltage-dependent failure rates and fault current-dependent failure rates to assess performance under both steady-state and transient conditions. Environmental considerations include carbon footprint analysis and the sustainable integration of RES. In Jayasinghe et al. [69], a multi-objective optimisation problem based on a genetic algorithm was formulated to minimise carbon emissions in a standalone DC microgrid. A carbon tax was incorporated into the final cost function to identify the most cost-effective and

Table 4
Reliability metrics and mathematical definitions for standalone DC microgrids Referenced from [96–98].

Metric	Description	Mathematical representation	Typical Use in planning of Standalone DC microgrids
LOLP	Probability that system generation cannot meet demand.	$LOLP = \frac{T_{LOL}}{T_{Total}}$	Evaluating adequacy of RES and storage sizing.
LOLE	Expected number of hours/days per year with unmet load.	$LOLE = \sum_{i=1}^{N_{LOL}} t_i$	Setting reliability targets for autonomous operation.
LPSP	Fraction of time the load is partially or fully unmet.	$LPSP = \frac{\sum_{t=1}^{T}(P_L(t) - P_G(t))_+}{\sum_{t=1}^{T} P_L(t)}$	Comparing renewable penetration and storage configurations.
ENS	Total energy demand unmet over an evaluation period.	$ENS = \sum_t (P_L(t) - P_G(t))_+$	Quantifying severity of supply shortfalls.
SAIDI	Average total duration of sustained interruptions per customer.	$SAIDI = \frac{\sum_i U_i}{N}$	Benchmarking against microgrid reliability norms.
SAIFI	Average number of interruptions per customer.	$SAIFI = \frac{\sum_i \lambda_i}{N}$	Assessing frequency of system disturbances/faults.
EENS	ENS weighted by component failure probabilities.	$EENS = \sum_{k=1}^{M} ENS_k . \mathrm{Pr}_k$	Long-term planning and probabilistic assessment.
Availability (A)	Probability that a component or system is operational.	$A = \frac{MTBF}{MTBF + MTTR}$	Evaluating converters, ESS, and network components.
RII	Quantifies variability of RES relative to its mean.	$RII = \frac{\sigma_{P_{RES}}}{\mu_{P_{RES}}}$	Deciding ESS capacity and reserve margins

DC = direct current; ESS = energy storage systems; ENS = energy not supplied; EENS = expected energy not supplied; LPSP = loss of power supply probability; LOLE = loss of load expectation; LOLP = loss of load probability; RES = renewable energy sources; RII = renewable intermittency index; SAIDI = system average interruption duration index; SAIFI = system average interruption frequency index; T_{LOL}= Total duration of loss-of-load events; N_{LOL}= Number of loss-of-load events; $P_L(t)$ = Load demand at time t; $P_G(t)$=Power supplied at time t; $x_+ = \max(x, 0)$; U_i = Outage duration expirieced by customer i; λ_i = Number of interruptions for customer I; Pr_k = Probability of contingency state k occurring; $MTBF$ = Mean Time between failures; $MTTR$ = Mean Time to Repair; $\mu_{P_{RES}}$, $\sigma_{P_{RES}}$= Mean and Standard deviation of Generation of RES.

environmentally sustainable alternative. Geographical factors such as land availability, accessibility, and proximity to load centres also play a critical role in microgrid planning [100].

5.4. Formation of optimal sizing problem

Various decision-support tools and optimisation frameworks have been developed to address these requirements and facilitate the microgrid planning process. Fig. 6 illustrates the formulation of the optimisation problem for designing a standalone DC microgrid.

Based on the assessments above, standalone DC microgrid planning involves defining specific objectives and constraints to optimise system design [101]. Common objectives include minimising operational costs, reducing energy losses, ensuring system reliability, and maximising RES utilisation. Constraints typically include resource availability, grid independence requirements, component limitations, and financial constraints. Some of the commonly used constraints are presented in Table 5. Various optimisation techniques, such as linear programming, mixed-integer programming, and metaheuristic algorithms, have been applied to solve microgrid planning problems. A multi-objective optimisation approach considers multiple objectives simultaneously, incorporating specific constraints to identify an optimal trade-off solution. This approach typically combines various objectives into a single composite function to determine a Pareto-optimal solution [102].

In Guo et al. [88], a multi-objective optimisation approach was applied to design a standalone DC microgrid for a remote area. The study considered 2 objectives: minimising total generation costs and maximising the IRR. A Pareto-optimal front was used to identify the most suitable design. In Ren et al. [90], a combination of the Non-dominated Sorting Genetic Algorithm-II algorithm and linear programming was employed to solve a standalone microgrid design problem using a multi-objective optimisation method. This approach enabled optimisation with more than 2 objectives. In the case study, the proposed method was used to optimise the design with 3 goals: reducing operational costs, minimising power losses, and lowering the load expectation ratio. Furthermore, Fadaee and Radzi [110] provide a comprehensive review of multi-objective optimisation methods used for designing standalone DC microgrids, analysing their effectiveness in addressing various design challenges.

Microgrid sizing involves determining the optimal location, capacity, and component selection to ensure system efficiency and reliability. Various approaches have been explored in the literature, including heuristic methods, AI based techniques, and hybrid optimisation frameworks. These methods aim to balance economic, technical, and environmental factors while accounting for uncertainties in energy generation and demand [111]. Studies have demonstrated that hybrid RES system designs can significantly enhance the performance of standalone microgrids. Additionally, recent advancements in

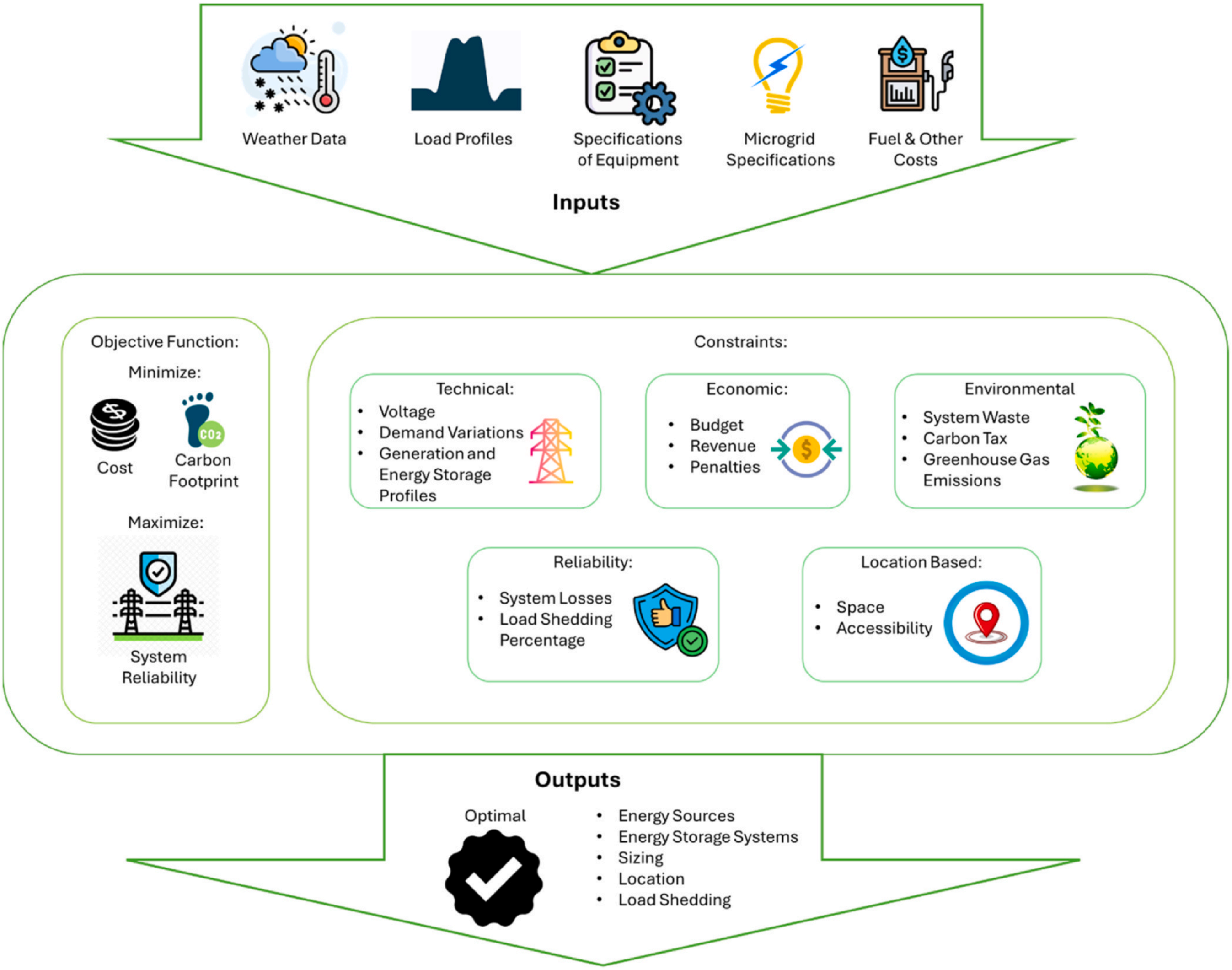


Fig. 6. Formulation of optimisation problem for the design of a standalone DC microgrid. DC = direct current.

Table 5
Commonly used constraints in standalone DC microgrid optimisation problems

Constraint	Type	Definition	Equation	Ref.
Boundaries of energy sources and ESS	Technical	Maximum and minimum power generated from energy sources, maximum and minimum SOC levels of ESS	$P_{G,Min} \le P_G(t) \le P_{G,Max}$ $SOC_{Min} \le SOC(t) \le SOC_{Max}$	[103]
FRE	Technical	Contribution of RES to the total energy supplied	$FRE = \frac{\sum E_{RG}}{\sum E_T}$	[104]
Generation– Demand– Storage Balance	Technical	Power from generation and ESS should match the demand	$P_G(t) + P_{ESS}(t) = P_D(t)$	[103]
LOLP	Reliability	Ratio between the annual energy deficit and the total demand	$LOLP = \frac{\sum_{i=1}^{365} EDef_i}{\sum_{i=1}^{365} ED_i}$	[105]
ELF	Reliability	Ratio between the effective period of load outages and the total operation time	$ELF = \frac{1}{T} \sum_{t=1}^{T} \frac{E[Q(t)]}{P_L(t)}$	[106]
REC	Reliability	Energy not supplied by RES due to low demand and limitations of ESS	$REC = \begin{cases} \sum_{t=1}^{T} [E_E - P_L(t)], P_L(t) < E_E \\ 0, \; P_L(t) \ge E_E \end{cases}$	[107]
SPL	Reliability	Probability of unmet load of the microgrid	$SPL = \frac{E_{Unmet}}{E_{Total}}$	[108]
LCOE	Economic	Unit cost of electricity considering all the costs involved, including future projected costs. LCOE should be less than a maximum value, which is the highest LCOE that the microgrid is economically feasible.	$LCOE = \frac{NPV_{Total\ Costs}}{Total\ Electricity\ Generated}$	[103]
PUCF	Environ-mental	Carbon footprint per unit of generated electricity	$PUCF = \frac{CF_{MG}}{E_{Total}}$	[109]

DC = direct current; ESS = energy storage systems; ELF = equivalent loss factor; FRE = fraction of renewable energy; LCOE = levelized cost of electricity; PUCF = per unit carbon footprint; REC = renewable energy curtailment; SPL = system performance level.

computational models and simulation tools have further improved microgrid planning methodologies.

5.5. Solving optimal sizing problem

For standalone DC microgrid sizing, several software tools can be utilised, with HOMER Pro, developed by the National Renewable Energy Laboratory (NREL), being the most widely used [112]. HOMER software leverages weather data from the selected location to determine the optimal microgrid size. It supports different objective functions, with the most common being the minimisation of the NPV of the microgrid's lifecycle cost [113]. The user must provide input data regarding the load profile and cost parameters.

In Oulis Rousis et al. [114], a standalone DC microgrid was designed using HOMER for a residential application, with no load shedding permitted. The optimal system configuration resulted in an NPV of \$56,264, which also corresponded to the least carbon-emitting solution. When accounting for carbon emissions, the most cost-effective option included the operation of RES hybridised with a standby diesel generator. In Raza et al. [115], a standalone microgrid for a remote village in Kharga Oasis, Egypt, was designed using HOMER Pro. The optimal configuration, consisting of solar PV, wind turbines, batteries, a diesel generator, and converters, achieved the lowest LCOE at \$0.10/kWh while ensuring zero unmet load demand. This design also reduced carbon emissions by 7.8% compared to a system relying solely on diesel generators. Another study in [116] demonstrated that electrifying a remote island in Hong Kong with a hybrid system consisting of PV, wind, and battery storage could effectively replace diesel generators while providing reliable energy to meet local demand.

The outcomes of an optimised standalone DC microgrid planning process include minimising costs, energy losses, and emissions while maximising revenue and system reliability [117]. Ongoing research continues to improve planning methodologies by incorporating advanced forecasting techniques and developing more robust optimisation frameworks. Future studies should investigate the potential of emerging technologies such as energy blockchain, P2P energy trading, and smart grid applications within standalone DC microgrids [118]. Furthermore, additional research is needed to evaluate the impact of ESS technologies and demand-side management strategies on enhancing system resilience and overall efficiency. EV charging stations and hydrogen fuel stations with on-site hydrogen production can be considered as integral components in the design of standalone DC microgrids. However, optimal integration of EV charging stations and hydrogen production systems in standalone DC microgrids has not been thoroughly explored in the literature. Therefore, future research can focus on how to effectively incorporate flexible loads such as EV charging and hydrogen production into the operation and planning of standalone DC microgrids.

6. Operation of standalone DC microgrids

The operation of standalone DC microgrids involves managing power generation, storage, and consumption within an isolated power system. It requires real-time coordination of RES, ESS, and prioritised loads to maintain voltage stability, optimise energy usage, and ensure uninterrupted supply [119]. To explain the decision-making framework within standalone DC microgrids, Fig. 7 presents a flowchart detailing the operational logic from input forecasting to control execution. The process begins with the acquisition of forecast inputs, including RES generation profiles, load demand predictions, and environmental conditions. These inputs feed into the EMS, which coordinates system-level decisions to ensure optimal performance [120]. Within the EMS, the load prioritisation sub-block first classifies electrical loads based on criticality and flexibility, enabling intelligent scheduling and shedding strategies. The output of this sub-block then informs the storage management sub-block, which determines optimal charging and discharging actions based on available energy, system constraints, and prioritised load requirements. The coordinated decisions from the EMS are then translated into control signals that govern the operation of DERs and load interfaces, ensuring reliable and efficient microgrid performance under varying conditions [121].

6.1. Energy management of standalone DC microgrids

Efficient and reliable operation of standalone DC microgrids requires a robust energy management strategy to optimise the utilisation of generation sources and ESS. Such strategies ensure that energy demand is met effectively while minimising losses and enhancing overall system performance. Energy management plays a critical role in the optimal allocation of resources, maintaining power stability, and ensuring balanced distribution within the microgrid. To prevent supply-demand imbalances and voltage fluctuations, energy sources, ESS, and loads must be continuously monitored and precisely coordinated.

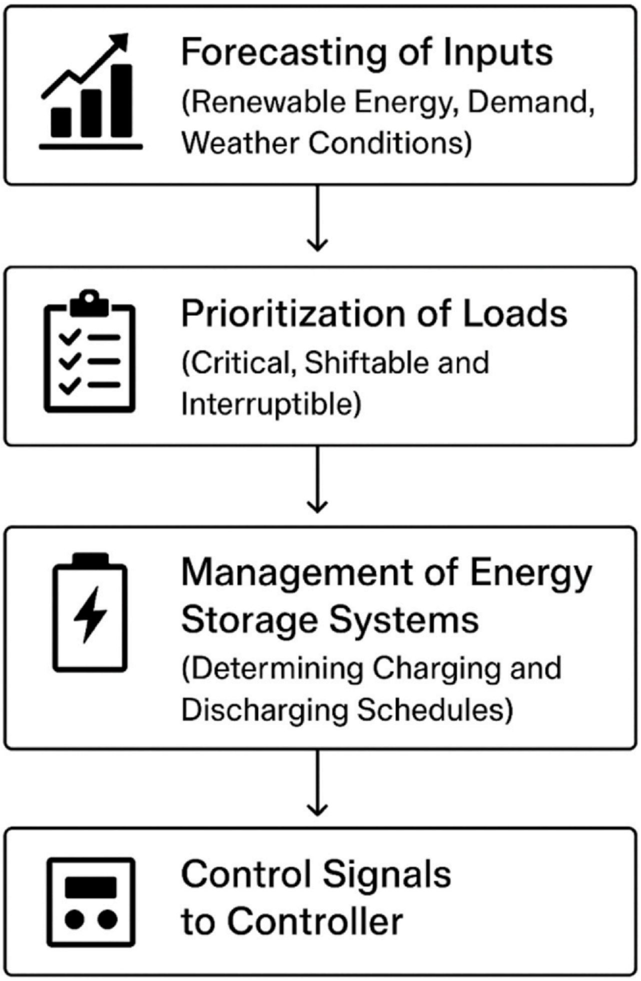


Fig. 7. Operation flow chart of standalone DC microgrids. DC = direct current.

An EMS, in conjunction with appropriate control strategies, facilitates the coordination of various components in standalone DC microgrids, enabling effective power allocation and distribution among them [122]. Techniques such as energy forecasting, load forecasting, demand-side management, and optimisation algorithms allow these microgrids to adapt to the stochastic nature of both generation and consumption patterns [123]. Energy management approaches employed to maintain power balance in standalone DC microgrids can be broadly classified into 4 categories: conventional methods, mathematical optimisation techniques, metaheuristic algorithms, and ML-based strategies, as illustrated in Fig. 8.

An AFLC algorithm for optimising the utilisation of multiple ESS in a standalone DC microgrid was proposed in Sinha and Bajpai [40]. The AFLC determines power sharing based on net power demand, the SoC of the controlled ESS, and the average SoC of all ESS in the primary bank. It enhances conventional FL control by preventing over- or under-utilisation of ESS. In Gil-González et al. [124], an SDP-based EMS was introduced to optimise the day-ahead operation scheduling of a standalone DC microgrid. The nonlinear programming problem is transformed into a convex optimisation model to minimise daily energy losses and carbon emissions. The robust SDP approach accounts for demand and supply uncertainties using a min–max strategy for worst-case energy management. Applied to a 27-bus DC microgrid, the SDP model outperforms random-based algorithms by achieving a global optimum.

In A.g et al. [125], an inverted zero-lag controller optimised using adaptive particle swarm optimisation (PSO) was proposed to stabilise bus voltage fluctuations in a standalone DC microgrid. Designed for optimal supercapacitor voltage regulation, the controller enhances system stability across a wide operating range. It reduces settling time by 22%–42% and peak overshoot by 15%–55% compared to conventional methods at lower supercapacitor voltages. In Bera et al. [126], an inverter-fed space vector-based droop control method with positive-negative sequence compensation and deep learning-based thermostatic load aggregation for DSM was introduced to mitigate voltage unbalance in a standalone DC microgrid while ensuring compliance with industry standards. This approach maintains voltage stability without compromising customer thermal comfort. Additionally, a novel one-time load registration method using an artificial neural network (ANN) simplifies the integration of new loads into DSM programmes. A detailed comparison of various energy management approaches for standalone DC microgrids is presented in Table 6.

In standalone DC microgrids, ancillary services such as voltage control, black start services, load balancing, spinning and non-spinning reserves, and power quality are provided through EMSs [127]. Voltage control in standalone DC microgrids has been extensively studied and continues to improve with technological advancements. However, other ancillary services in standalone DC microgrids, such as black start capabilities, reserves, and power quality, have been largely overlooked in the literature, despite their importance for ensuring smooth operation and facilitating emergency responses. Therefore, future research should also focus on these areas.

6.2. *Control strategies of standalone DC microgrids*

Maintaining DC bus voltage within specified thresholds is crucial for preserving power quality and preventing equipment damage [128]. A well-designed control algorithm with an integrated energy management strategy must balance power flow and regulate DC bus voltage. Due to the intermittent nature of RES, advanced control algorithms, predictive modelling, and real-time monitoring are essential for efficient energy dispatch in standalone DC microgrids. The resilience of microgrids is further enhanced by integrating intelligent control systems with energy and demand forecasting, along with robust communication networks [129]. These advancements enable microgrids to achieve optimal performance in dynamic environments. Fig. 9 summarises the key control strategies used in standalone DC microgrids.

The control of standalone DC microgrids is categorised into 3 primary strategies: decentralised control, centralised control, and distributed control. Conceptual diagrams illustrating these strategies are presented in Fig. 10.

6.2.1. *Decentralised control*

Decentralised control of standalone DC microgrids is a strategy in which decision-making is distributed among local controllers. Each controller acquires input signals from local measurements, processes them, and generates the appropriate control signals for the connected equipment [55]. This approach operates independently of a communication network between controllers and does not require a central microgrid controller. Among decentralised strategies, droop control is the most widely implemented, with droop parameters critically influencing system stability, control signal damping, and power-sharing accuracy. Specifically, lower droop parameters can lead to slower damping and reduced accuracy in power sharing, whereas higher droop parameters may destabilise the DC link voltage [130]. As a result, the proper tuning of these parameters presents a significant challenge. To address this, various droop control strategies have been proposed to optimise parameter selection and improve the overall performance of standalone DC microgrids, as discussed in the following subsections.

6.2.1.1. Conventional droop control. Conventional droop control decreases the DC bus voltage reference as the output current increases, as expressed in Eq. (1). In this equation, $(V_{DC})_n$, $(I_{DC})_n$, and $(R_{DC})_n$ represent the output voltage, output current, and virtual

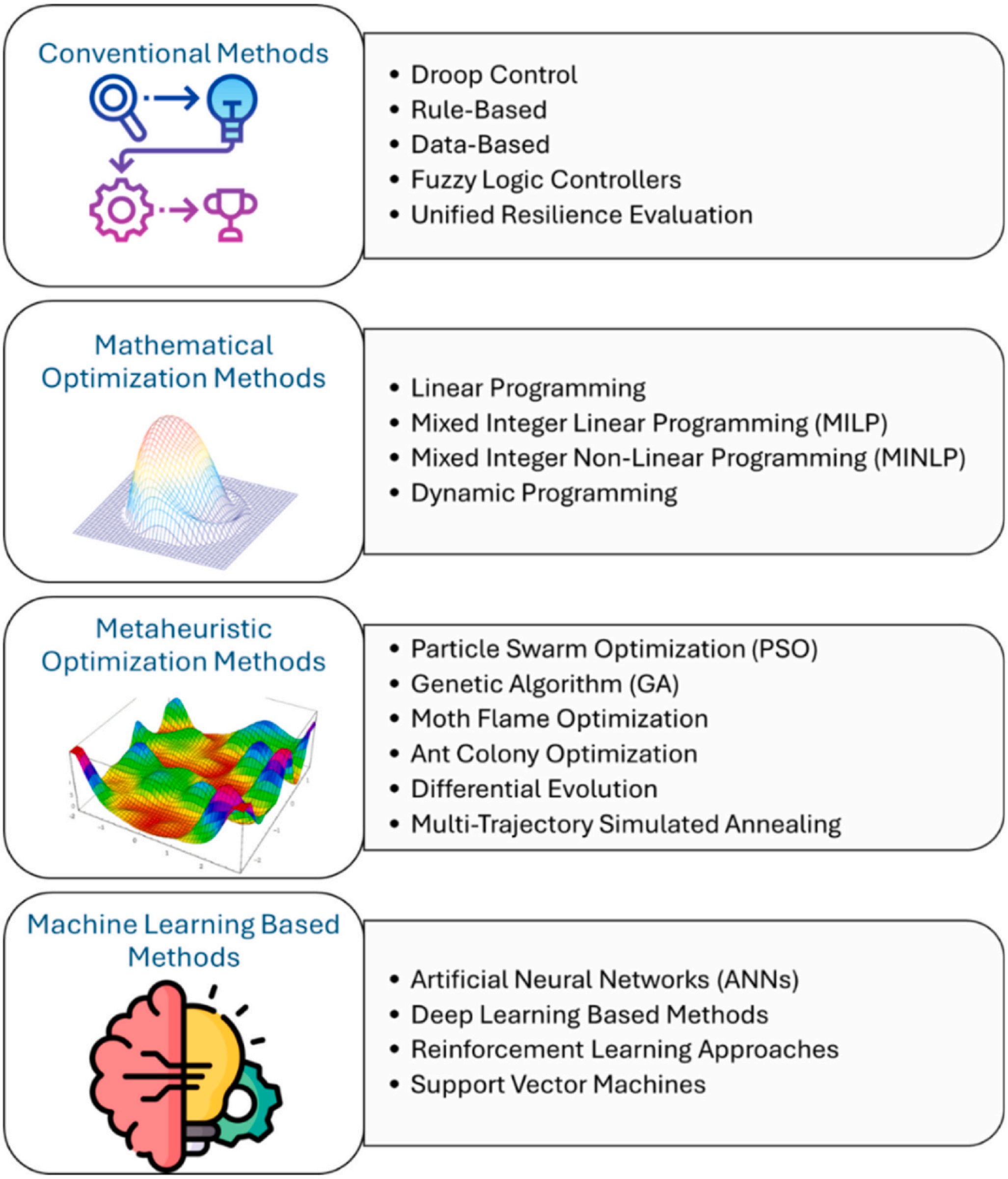


Fig. 8. Classification of energy management algorithms in standalone DC microgrids. DC = direct current.

resistance of each converter unit, respectively, while $V_{DC}{}^*$ denotes the reference DC bus voltage. However, due to the varying voltage drops across line resistances, this approach can compromise both current-sharing accuracy and voltage regulation [131].

$$(V_{DC})_n = V_{DC}{}^* - (R_V)_n (I_{DC})_n \tag{1}$$

6.2.1.2. Adaptive droop control. Adaptive droop control is employed in standalone DC microgrids to regulate the DC bus voltage while enabling load sharing among multiple converters without requiring communication [132]. Unlike conventional droop control, where the voltage reference decreases linearly with output current, adaptive droop control dynamically adjusts the virtual resistance based on system conditions to enhance voltage regulation and minimise circulating currents [133]. The output voltage of each controller under adaptive droop control is described by Eq. (2), where k_V is the adaptive gain that modulates the droop slope in response to voltage deviations, and R_{V0} denotes the nominal droop resistance.

$$(V_{DC})_n = V_{DC}{}^* - R_{V0}.\ [1 + k_V (V_{DC}{}^* - V_{DC})] \tag{2}$$

Adaptive droop control allows for enhanced load sharing and improved voltage stability, particularly under varying load and generation conditions typical of standalone DC microgrids [134]. In Habibullah and Kim [135], an adaptive droop control with constant voltage regulation is proposed for DC microgrids with multiple sources. The method adaptively adjusts droop characteristics based on electricity prices and SOC levels to optimise operational flexibility and costs, ensuring reliable power-sharing without communication links while maintaining stable DC bus voltage. Simulation and experimental results demonstrate the effectiveness and overall performance of the proposed decentralised control scheme.

Augustine et al. [136] propose a fault detection and control scheme for standalone solar-PV DC microgrids, combining current-derivative and differential/overcurrent methods to identify and classify faults. An adaptive droop strategy manages fault currents and converter output, while DC circuit breakers isolate faulty components. Simulation results demonstrate effective fault control and improved protection performance. In [137], an adaptive droop control method with continuous voltage regulation was introduced, in which droop characteristics are adaptively adjusted based on the availability of renewable energy and the SOC levels of the ESS.

Table 6
Comparative analysis of different energy management approaches applicable to standalone DC microgrids

Energy management approach	Advantages	Disadvantages	Suitable applications
Conventional methods	• Simple and well-established. • Faster response and real-time implementation • Less computational burden. • Plug and play capability	• Not always optimal. • Limited adaptability to dynamic conditions • Requires expert knowledge and manual tuning.	• Small-scale DC microgrids with fixed configurations. • Systems where simplicity and real-time operation are essential.
Mathematical optimisation methods	• Globally optimal solutions. • Can consider multiple objectives • Well-suited for day-ahead scheduling	• High computational burden. • Requirement of accurate system models, which may be challenging to obtain. • Scalability issues	• Day ahead or long-term planning. • Systems where optimality is essential.
Metaheuristic optimisation methods	• Can handle non-linear, non-convex problems. • More adaptable to dynamic conditions • Flexibility in mathematical models	• High computational burden. • Not guaranteed to find global optimum. • May require fine-tuning	• Day-ahead planning where exact models are not available. • Complex microgrids with non-linear constraints
ML-based methods	• Adaptive and self-learning • Suitable for real-time energy management in dynamic environments • Can handle uncertainties in inputs	• Requirement of a large amount of training data • High computational burden. • Black-box nature • May require periodic re-training	• Real-time energy management in complex and unpredictable environments • Standalone DC microgrids with high renewable penetration • Adaptive DSM strategies.

DC = direct current; DSM = demand side management; ML = machine learning.

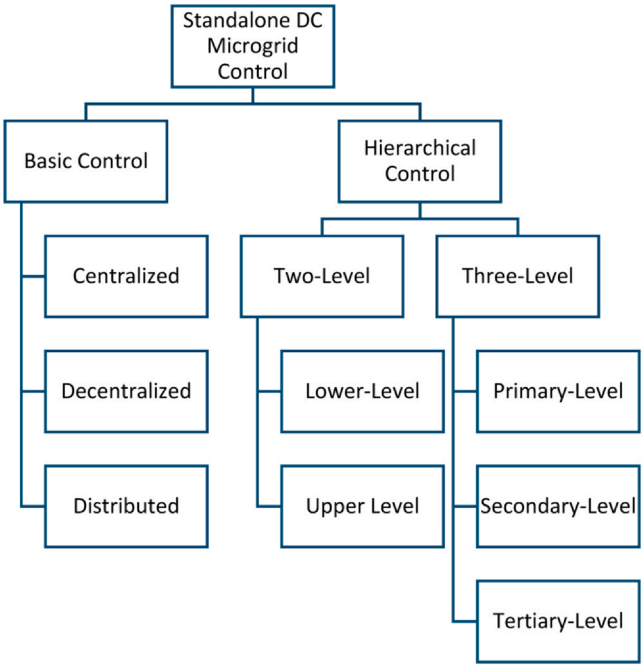


Fig. 9. Categorisation of control topologies of standalone DC microgrids. DC = direct current.

6.2.1.3. Mode-triggered adaptive droop control. Mode-triggered adaptive droop control is an advanced load sharing and voltage regulation strategy designed to enhance the operational robustness of standalone DC microgrids [138]. Unlike conventional droop methods that rely on a fixed virtual resistance, this approach employs a set of discrete droop modes that are activated in response to specific operating conditions [139]. The controller dynamically selects the appropriate droop coefficient based on indicators such as load level, bus voltage deviation, and transient or fault events, thereby improving overall system performance [140].

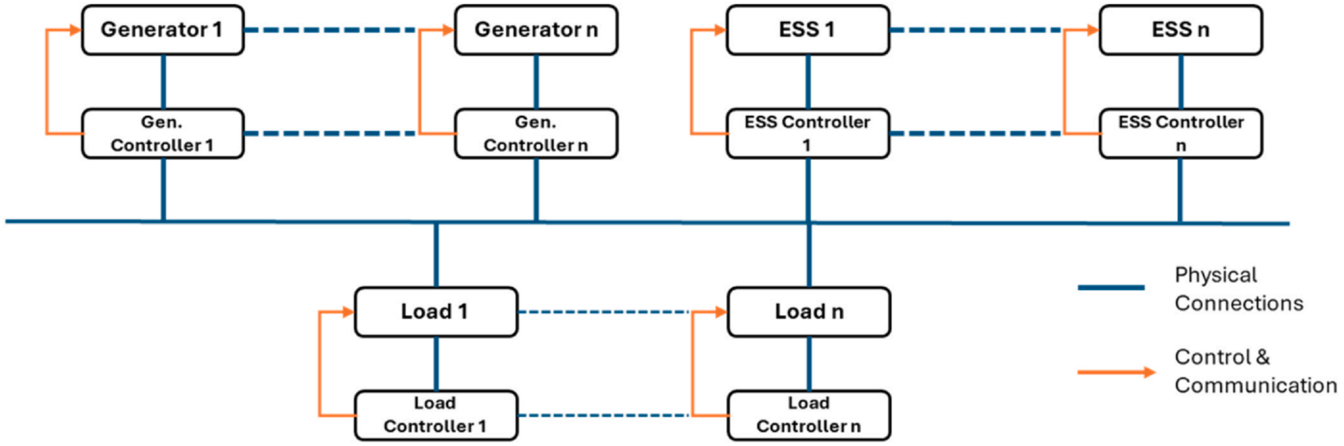
The voltage reference of converter n is typically expressed by Equation (3), where $R_{DP}(m)$ denotes the mode-dependent droop resistance and m represents the active operating mode. A mode-selection logic governs the transitions between these operating modes. An example of such logic is provided in Eq. (4), where ε and I_{Th} are the predefined thresholds for bus-voltage deviation and converter current, respectively, and V_{Flt} denotes the fault-level voltage deviation of the DC bus.

$$(V_{DC})_n = V_{DC}{}^{*} - R_{DP}(m)(I_{DC})_n \tag{3}$$

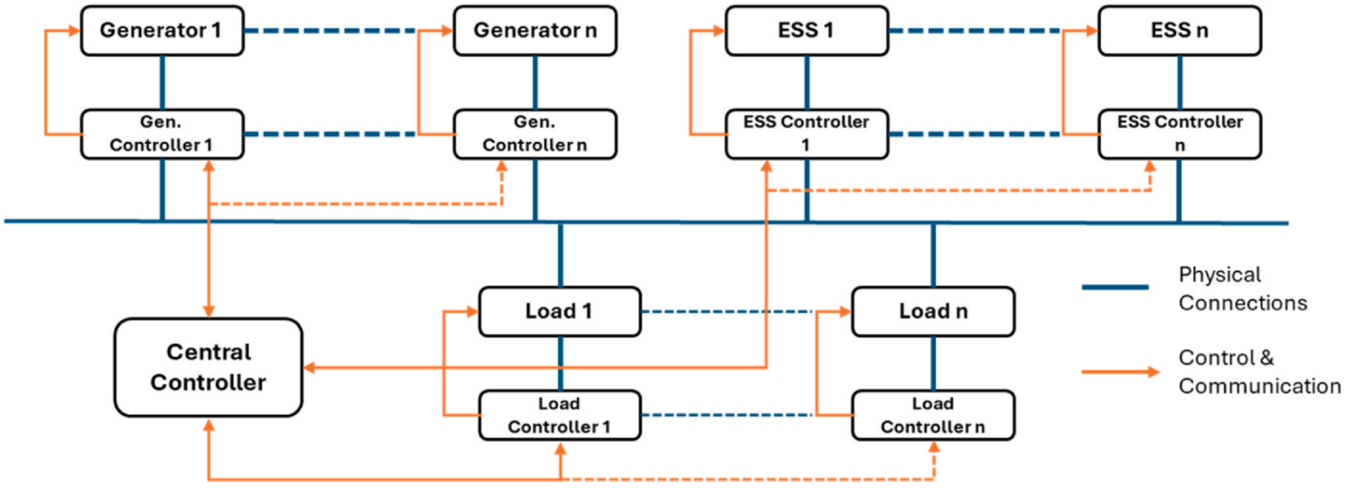
$$m = \begin{cases} 1,\ if\ |V_{DC}{}^{*} - V_{DC}| < \varepsilon,\ and (I_{DC})_n < I_{Th} \\ 2,\ if\ |V_{DC}{}^{*} - V_{DC}| \geq \varepsilon,\ and (I_{DC})_n \geq I_{Th} \\ \qquad 3,\ if V_{DC} < V_{Flt} \end{cases} \tag{4}$$

This mode-triggered adaptation enhances voltage regulation during normal operation, improves current-sharing accuracy under high-demand scenarios, reduces circulating currents during transients, and provides an inherent protective response during abnormal or fault conditions [141]. Consequently, it offers a flexible and effective control framework for maintaining stability and power quality in standalone DC microgrids. In Han et al. [142], a decentralised energy management strategy is introduced for standalone DC microgrids, addressing the added complexity and control challenges introduced by hydrogen subsystems. The approach combines autonomous mode division, classifying the microgrid into 8 operating modes using only local measurements, with an adaptive droop scheme that coordinates distributed units without communication.

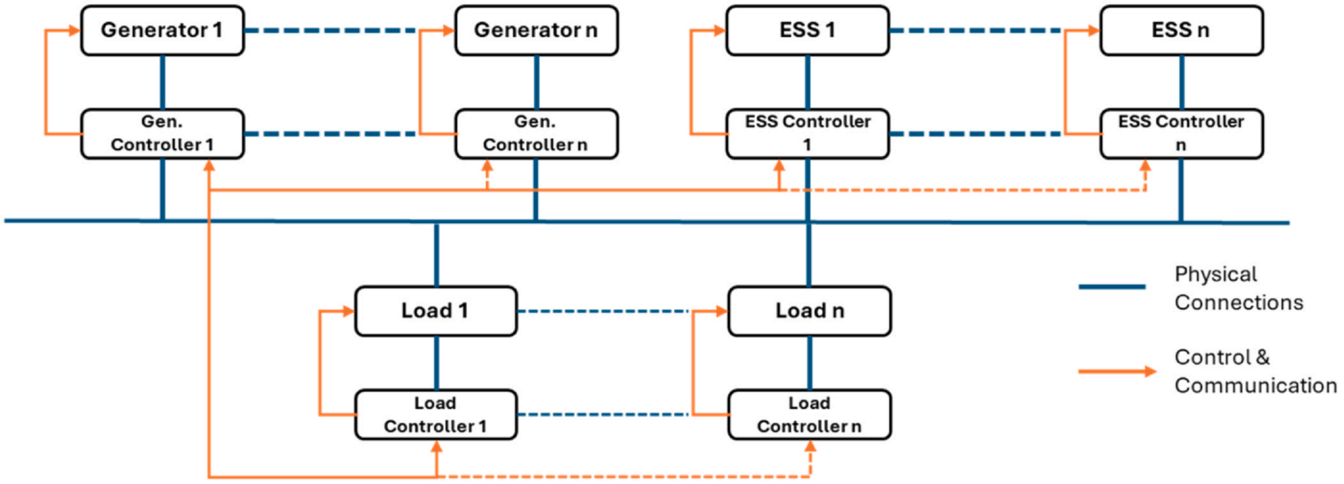
Mode-triggered adaptive droop control leverages technologies such as fuzzy logic and active damping to enhance the overall performance. In Veysi et al. [143], a droop-based sliding mode controller is developed to improve power sharing and voltage regulation in isolated DC microgrids under uncertainties and disturbances. The approach integrates an improved nonlinear droop model with fuzzy-based parameter adjustment to reduce control stress while maintaining communication-free operation. A dual-mode droop-based power regulation strategy is proposed in Pan et al. [144] for islanded PV–battery DC microgrids to handle sudden load changes with seamless transitions. Mode 1 maintains stable battery charging, while Mode 2 prioritises PV utilisation when load demand exceeds PV output, with both modes coordinating bus-voltage support. The instability introduced by current disturbance-based islanding detection in DC microgrids is discussed in Shi et al. [145], which develops an impedance model to clarify the interaction between the voltage source converter and distributed generators. A notch-filter-based active damping strategy is then proposed to enhance system stability and detection speed without relying on communication, with experimental results verifying its effectiveness.



(a) Decentralized Control



(b) Centralized Control



(c) Distributed Control

Fig. 10. Conceptual diagrams of basic control topologies of standalone DC microgrids. DC = direct current; ESS = energy storage systems.

6.2.1.4. AI/ML-based droop control. AI and ML techniques are increasingly applied to droop control in standalone DC microgrids to enable adaptive and predictive voltage and power-sharing management [146]. These AI/ML-based controllers dynamically optimise droop coefficients in real time, improving stability and load-sharing under variable operating conditions [147]. These approaches can forecast load variations, mitigate voltage deviations, and reduce reliance on extensive communication infrastructure [148].

Studies show that AI/ML-enhanced droop control significantly improves transient response, robustness to disturbances, and overall microgrid efficiency, offering a promising pathway for autonomous standalone DC microgrid operation. In Saeidinia et al. [149], an ML-based optimised droop control method is proposed for DC microgrids to simultaneously minimise production cost and power line losses, overcoming the limitations of conventional hybrid droop schemes that require arbitrary weighting adjustments. The approach leverages AI for accurate prediction of costs and losses and employs gradient descent optimisation, with effectiveness validated through comparisons under scenarios including rapid load changes. A ML-enhanced microgrid control framework is proposed in Abo-Elkhair et al. [150], which integrates ANNs and reinforcement learning with traditional PI controllers to dynamically optimise controller parameters and improve stability under renewable energy integration. Simulation results show that ML-based controllers significantly reduce voltage THD, improve settling time by 75%, and enhance frequency stability by 93%, outperforming conventional techniques.

6.2.2. *Centralised control*

Centralised control of standalone DC microgrids integrates control distribution through communication methods, enabling coordinated operation. In this approach, local controllers transmit input data to a central unit, which analyses the information and generates control signals for individual controller units. This strategy requires a dedicated central controller for the microgrid and point-to-point communication links between the central controller and all DC microgrid components [151]. The utilisation of centralised control in DC microgrids offers notable advantages over decentralised control, including improved system coordination, enhanced voltage regulation, and more precise power-sharing capabilities.

In Abdullahi and Jin [152], a centralised controller was proposed to minimise voltage estimation errors by combining deterministic modelling, linear Kalman filtering-based voltage estimation, and a linear quadratic regulator for system stabilisation. Integral action was incorporated to eliminate voltage errors during transients, while a feedback control rule and the Riccati equation refined the controller design. A coordinated control approach was introduced in Wu et al. [153], integrating a primary controller based on the bus signalling method with a secondary centralised controller. This system ensures that the ESS operates within predefined SOC limits while effectively regulating DC bus voltage. In Cupelli et al. [154], Linear Quadratic Gaussian and synergetic controllers were employed, demonstrating their effectiveness in stabilising the system during significant load disturbances.

This centralised control approach has several drawbacks. The requirement for a dedicated central microgrid controller and point-to-point communication links with equipment reduces system reliability and flexibility while making it vulnerable to single points of failure. Additionally, the overall system cost is high due to the extensive communication infrastructure required for real-time data exchange between the central and local controllers [118]. Moreover, the central controller must collect and process a large volume of data from all DG units, which can lead to computational overload as the number of DG units increases [155]. Furthermore, system scalability is limited, as expansion depends directly on the central controller, making it rigid and less adaptable to growing energy demands.

While decentralised and centralised control paradigms in standalone DC microgrids respectively emphasise local autonomy and global supervisory coordination, the emerging distributed control framework seeks to integrate the benefits of both by employing multi-agent systems, consensus-based algorithms, and real-time data exchange to achieve scalable, resilient, and adaptive control across DERs and power electronic interfaces [156].

6.2.3. *Distributed control*

Compared to centralised and decentralised control approaches, the distributed control approach offers several advantages. It distributes decision-making among local controllers while enabling information sharing between them, enhancing fault tolerance and resilience in standalone DC microgrids [157]. This approach also improves scalability and facilitates the seamless integration of new components with minimal effort. Different types of distributed control methodologies have been found in the literature as mentioned in the following subsections.

6.2.3.1. DC bus signalling-based control. DC bus signalling–based control provides a fully distributed coordination mechanism for standalone DC microgrids, where predefined bus-voltage thresholds trigger mode transitions of source and storage interface converters without requiring communication links. By encoding system conditions through intentional voltage deviations, converters autonomously switch between constant-voltage or constant-power modes to maintain stable operation [158]. Although highly reliable and plug-and-play in compact systems, its performance is limited by line voltage drops, making it most effective in nanogrids or microgrids with short distribution feeders [159].

In [160], the stability of standalone DC microgrids is enhanced by an improved distributed DC-bus signalling control strategy for PV converters, reducing dependence on the BESS by intelligently managing PV output power. The method switches PVs between maximum power point tracking and voltage-regulating modes based on DC-bus voltage, preventing shutdowns during BESS absence and minimising voltage oscillations. In [161], a novel DC-bus signalling–based power management strategy is proposed for an islanded DC microgrid with two subgrids connected via an IBD, using droop control of batteries based on charging/discharging power and SOC to regulate DC bus voltages. The method coordinates generation and storage without relying on communication lines, shares power through the IBD, and applies load curtailment under overload.

6.2.3.2. Distributed cooperative control. Distributed cooperative control enables coordinated regulation of voltage, power sharing, and energy management in standalone DC microgrids through local communication among converters. Using multi-agent or consensus-based algorithms, ESS can collaboratively manage SOC and voltage levels to prevent energy deficit and enhance system reliability [162]. This approach supports unified control across different operating modes without relying on DC bus signalling and allows optimal coordination of distributed resources while maintaining a stable average bus voltage [163]. However, its effectiveness depends on reliable low-latency communication and careful design of cooperative interaction rules [164].

A distributed model-based cooperative controller is proposed in Hanzaei et al. [165] to enhance voltage synchronisation in standalone DC microgrids. This controller employs an integral-based linear-quadratic regulator that synchronises both output voltages and their derivatives using the second-order voltage dynamics of DC-DC buck converters. The approach reduces voltage ripples, eliminates steady-state errors, and ensures global system stability based on Lyapunov stability theory. In Cheng et al. [166], a distributed fixed-time secondary control strategy has been introduced to enable simultaneous average voltage restoration. A voltage observer is designed to estimate the average voltage, while a fixed-time voltage regulator restores the average voltage by adjusting the primary control input. In Peng et al. [167], a distributed optimal control scheme for DC microgrids has been developed to minimise generation costs while regulating individual bus voltages. By formulating an optimal control problem and deriving necessary optimality conditions, the proposed controller ensures dynamic convergence to cost-minimising operating points while maintaining voltage stability through Lyapunov synthesis.

6.2.3.3. Average voltage sharing. Average voltage sharing with pilot-bus regulation is a distributed secondary control method designed to improve voltage uniformity and restore the nominal bus voltage in standalone DC microgrids. In this scheme, each converter generates a local secondary control signal, and the average of these signals is used to adjust the primary voltage reference, thereby regulating the designated pilot-bus voltage [168]. Anti-windup mechanisms are often incorporated to prevent compensator saturation and ensure stable operation under dynamic conditions. While the method enhances coordinated voltage restoration across all units, its implementation still requires a low-bandwidth communication link to exchange control signals among distributed converters [169].

In Wang et al. [170], an adaptive fixed-time cascaded distributed control strategy is proposed for bipolar standalone DC microgrids to ensure current sharing, voltage regulation, and time delay resilience. This approach achieves fixed-time convergence and enhances practicality by incorporating intermediate variable information exchange, proportional control, and an adaptive rule for control gain selection. Furthermore, a distributed secondary control scheme using LADRC is proposed in Liu et al. [171] to improve voltage regulation and current sharing in DC microgrids. The LADRC-based voltage controller compensates for voltage deviations, while the current controller eliminates variations in output impedance between converters, thereby enhancing current-sharing accuracy.

6.2.3.4. Average current sharing. Average current sharing is a communication-assisted distributed control strategy that enhances voltage regulation and improves load-sharing accuracy among parallel converters in standalone DC microgrids. In this method, converters exchange their digitally measured output currents to compute an average current reference, which is then used to adjust the voltage reference through an additional compensating term [172]. By shifting the droop characteristics along the voltage axis, the modified voltage reference is driven closer to the nominal value as system load varies, thereby reducing voltage deviation while maintaining proportional load sharing [173]. This approach significantly improves sharing precision, though it requires reliable communication and synchronised current sampling to ensure stable and effective operation [174].

A distributed control system based on an event-triggered average consensus protocol and fractional-order proportional-integral controllers was proposed in Doostinia et al. [175] to achieve voltage stabilisation and energy balancing of ESSs. This strategy reduces network load, while the secondary controller compensates for voltage offsets and balances ESS energy levels. A distributed finite-time event-triggered secondary control approach is introduced in Cho and Bidram [176], to ensure accurate current sharing and critical bus voltage regulation without requiring periodic communications. This approach enhances convergence speed and transient response while reducing communication network burdens.

Table 7 presents a comparison of the benefits and drawbacks of different control strategies for standalone DC microgrids, which is influenced by [177–179].

Decentralised, centralised, and distributed control strategies each offer unique advantages in managing standalone DC microgrids, addressing trade-offs between autonomy, communication overhead, scalability, and fault tolerance. While decentralised control enhances system resilience through local decision-making, centralised schemes facilitate global optimisation, and distributed methods strike a balance by enabling peer-to-peer coordination. Building upon these paradigms, hierarchical control integrates their strengths into a structured multi-tier architecture, typically comprising primary, secondary, and tertiary layers, that enables fine-grained regulation of voltage and current at the device level, dynamic load sharing among distributed generators, and optimal power flow scheduling informed by system-wide objectives and constraints.

6.2.4. Hierarchical control

Hierarchical control framework is a functionality-based, generic method typically consisting of 3 levels of control, i.e. primary, secondary, and tertiary, designed to coordinate various components within DC microgrids [180]. For standalone DC microgrids, implementing hierarchical control is beneficial for maintaining stable voltage regulation, enabling seamless power-sharing among diverse energy sources, and optimising energy utilisation [181]. The integration of these control layers enhances the microgrid's resilience against fluctuations in renewable generation and load demand, thereby improving the system's autonomy and reliability. Fig. 11 illustrates the architecture of hierarchical control in standalone DC microgrids.

6.2.4.1. Primary control. At the lowest level, primary control operates in a decentralised manner to regulate voltage and current while ensuring proper power-sharing among DER. This is commonly achieved through droop control or virtual impedance methods [128]. The primary controller relies on local measurements to regulate the DC link voltage and responds more rapidly than secondary and tertiary controllers, which primarily manage power flow. A virtual resistance model, characterised by zero power loss and immunity to external conditions, is often used to model droop control behaviour [182]. The most widely used droop control strategies include current-mode droop methods and voltage-mode droop methods, which utilise I-V and P-V control techniques, respectively. As primary control is decentralised, it enhances system reliability and modularity. However, selecting droop parameters involves a trade-off between voltage regulation and power-sharing accuracy [183]. Low droop parameters improve voltage regulation but reduce power-sharing accuracy, whereas high droop parameters enhance power sharing but lead to poor voltage regulation [36]. Therefore, secondary control is required to mitigate the limitations of primary control.

6.2.4.2. Secondary control. Hierarchical control framework employs secondary control to improve power-sharing accuracy and voltage regulation, addressing the limitations of primary control [184]. When high line resistance exists due to long feeders, the performance of primary control may degrade. The secondary controller integrates advanced control functions and generates reference signals for voltage and current, which are then transmitted to the primary controller [185]. By utilising these signals, the primary controller enhances system reliability, voltage stability, power-sharing

Table 7
Comparison of characteristics of different control strategies for standalone DC microgrids

Characteristics	Decentralised control	Centralised control	Distributed control
Reliability	High	Low (prone to a single point of failure)	High
Scalability	High	Limited	High
Communication	Local (power control)	Global (data packets)	Hybrid
Modularity	High	Low	High
Computational burden	Low	High	Moderate
Response time	Fast	Slow	Moderate
Coordination and resource allocation	May be suboptimal	Optimal	Optimal
Resilience against cyber attacks	High	Low	Moderate
Implementation	Complex	Simpler	Complex

DC = direct current.

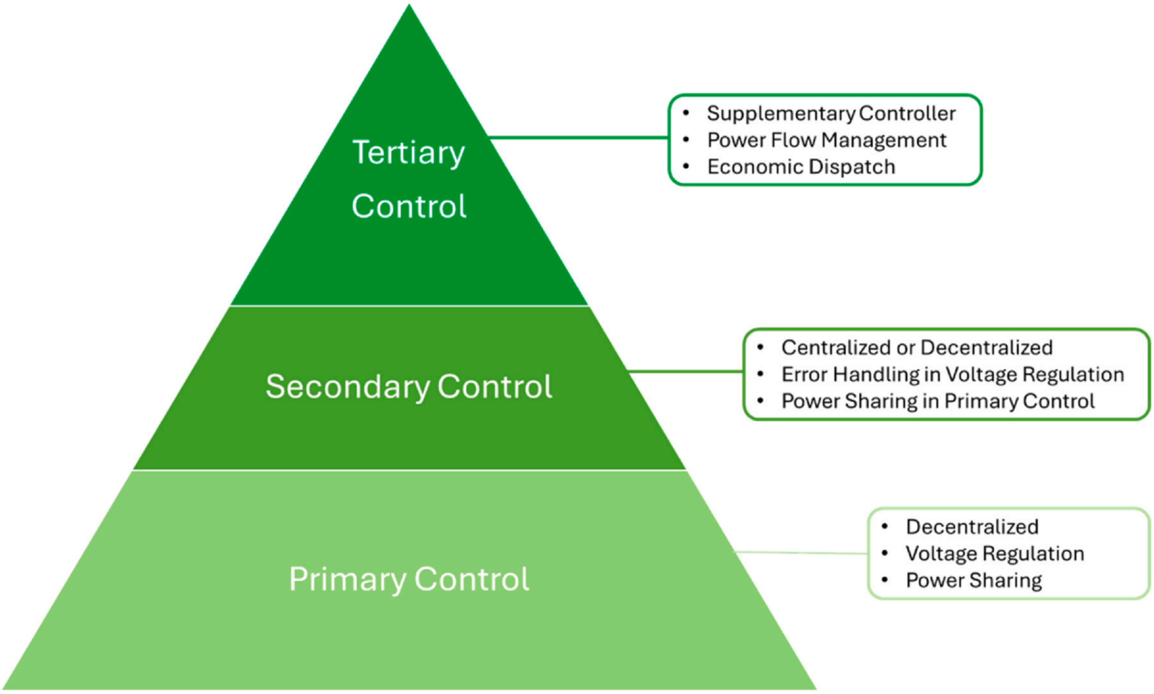


Fig. 11. Architecture of hierarchical control.

efficiency, and overall power quality in DC microgrids [186]. In this framework, a centralised controller typically defines the DC voltage and communicates it to voltage-regulated converters. However, the reliability and robustness of the centralised controller can be compromised due to its dependence on a communication network [187]. To address these challenges, some secondary controllers adopt a distributed control approach, improving fault tolerance and scalability [188]. In some instances, a decentralised controller is employed at the secondary level to reduce system complexity and minimise communication requirements.

6.2.4.3. Tertiary control. The tertiary controller plays a key role in ensuring cost-efficient operation and comprehensive regulation of standalone DC microgrids, functioning as a supplementary controller. Although these microgrids are significantly smaller than conventional power grids, they still require efficient power flow management and economic dispatch, which the tertiary controller facilitates [189]. The primary objective of the tertiary controller is to coordinate power exchange among interconnected microgrids and between DERs within a single microgrid. To optimise microgrid scheduling, the tertiary controller employs heuristic algorithms such as PSO [23]. In Abdelhadi et al. [190], an AI-based control technique and proposes a novel hybrid optimisation method, termed HYCHOPSO, which integrates CHO and PSO, has been used for tertiary control of multiple standalone DC microgrids. Complete implementation of primary, secondary, and tertiary controllers forms the most optimal control strategy for ensuring microgrid stability while minimising operational costs. However, research on applying all 3 hierarchical control levels specifically to standalone DC microgrids remains limited. Further investigation is necessary to explore optimal integration of these control layers. Additionally, incorporating them into the EMS using emerging technologies such as AI, ML, energy trading, and blockchain offers a promising direction for future studies.

The most promising approaches for DC bus voltage regulation in standalone DC microgrids are hybrid hierarchical architectures that combine a communication-free primary layer with a communication-assisted distributed secondary layer and a supervisory tertiary optimiser [191]. At the primary level, adaptive and mode-triggered droop variants provide robust, fast local response and reduce circulating currents compared with fixed droop, preserving stability during transients and faults. Where feeder resistances and steady-state offsets degrade primary performance, a distributed secondary controller that uses low-bandwidth signal exchange restores nominal bus voltage and corrects power-sharing errors without creating a central single point of failure. Finally, AI/ML methods and tertiary optimisation can improve performance further by forecasting generation/load and adaptively tuning droop/secondary gains for efficiency and transient performance [192]. In practice, this layered hybrid strategy offers the best trade-off between fast local dynamics, accurate voltage restoration, scalability, and resilience against single-point failures and communication outages.

7. Uncertainty management of standalone DC microgrids

Uncertainty management in standalone DC microgrids involves identifying, modelling, and mitigating the impact of unpredictable variations in renewable generation, load demand, component ageing, and environmental conditions to maintain reliable and cost-effective operation [193]. Unlike grid-connected systems, standalone DC microgrids, especially those deployed in remote or offshore environments, must rely solely on local generation and storage, making them highly sensitive to forecasting errors and resource variability [194]. Key uncertainties include solar and wind intermittency, short-term load fluctuations, temperature-dependent ESS degradation, and intermittent failures of power electronic converters [195]. These uncertainties affect both operational scheduling and long-term planning, necessitating systematic mitigation strategies beginning from the design phase.

Robust uncertainty modelling in standalone DC microgrids requires reliable benchmark datasets and statistically grounded representations of RES, load behaviour, and component ageing. In recent literature, solar irradiance uncertainty is commonly characterised using high-resolution datasets such as the NSRDB or PVGIS, supported by site-measured irradiance when available, enabling time-series modelling at 1–15-min granularity for probabilistic PV output prediction [196]. Wind-speed uncertainty is typically represented using long-term measurements from the NREL WIND Toolkit or local met-mast data, which allow accurate parameterisation of Weibull or Rayleigh distributions for scenario-based wind-power modelling [197].

Table 8

Representative datasets and modelling practices for key uncertain variables.

Uncertain parameter	Representative datasets/models	Typical temporal resolution	Typical usage in literature	Ref.
Solar irradaince	NSRDB, PVGIS, site-specific irradiance measurements, local databases such as BoM, NIWA	1–15 min	Probabilistic forecasting, Scenario generation	[201], [202]
Wind speed	NREL WIND toolkit, local met-mast dataset, local databases such as BoM, NIWA	1–15 min	Weibull or Rayleigh modelling, Stochastic wind-power scenarios	[203]
Load demand	Historical load profiles in facility level	1–15 min	Short-term load forecating, Demand response modelling	[204]
ESS degradation	Manufacturer cycle life data, Lab-based ageing data	Hourly / Daily	Battery ageing modelling, Degradation-aware scheduling	[205]
Reliability of converters	Empirical failure rate databases, testbed measurements	Event based	Reliability assessment, Resilience analysis, Protection studies	[206]

ESS = energy storage systems; NREL = National Renewable Energy Laboratory; NSRDB = National Solar Radiation Database; PVGIS = photovoltaic geographical information system.

The load demand variability is frequently captured using historical consumption profiles sampled at 5–15-minute intervals, supporting both short-term load forecasting and the development of realistic demand-response strategies [198]. ESS degradation uncertainty is modelled using cycle life datasets provided by manufacturers or laboratory-derived ageing curves, allowing integration of temperature, depth-of-discharge, and calendar-ageing effects into operational and planning analysis [199]. Uncertainty associated with converter reliability is typically incorporated through empirical failure-rate datasets or hardware-in-the-loop testbed measurements, which support resilience assessment and fault-tolerant control design [200]. Table 8 summarises the representative datasets and modelling practices employed for key uncertain parameters in standalone DC microgrids.

Handling uncertainty in standalone DC microgrids requires the integration of advanced modelling, forecasting, and control strategies to maintain reliable and efficient operation under highly variable operating conditions [207]. As illustrated in Fig. 12, existing uncertainty management approaches can be broadly classified into 6 major categories. This section provides a structured synthesis of these methods, emphasising key benchmarking aspects, namely, the origin and quality of datasets used for model development, the forecasting and control horizons employed, reported prediction or optimisation error levels, and the scenario generation techniques used to represent stochastic variations in renewable generation, load demand, and environmental conditions.

7.1. Stochastic optimisation

Stochastic optimisation has emerged as a foundational approach for uncertainty management in standalone DC microgrids, offering a mathematically rigorous framework that explicitly incorporates randomness in renewable generation, load demand, market variables, and component behaviour [208]. Unlike deterministic optimisation, which relies on point forecasts and fixed inputs, stochastic methods model uncertain parameters, such as solar irradiance, wind power, or load demand, using probability distributions or scenario sets derived from historical data, Monte Carlo sampling, or ML-based probabilistic forecasting [209].

In general, a 2-stage stochastic optimisation problem can be formulated as shown in Eq. (5), where x represents the first stage decisions, typically including storage scheduling, generator dispatch commitments, or load allocation, while ω denotes the set of scenarios characterising underlying uncertainties [210]. The term $C(x)$ corresponds to the deterministic cost associated with first-stage decisions, and $Q(x,\omega)$ represents the scenario-dependent recourse cost. The second stage (recourse) problem is commonly defined as in Eq. (6) and ensures feasibility for each scenario through operational adjustments y_ω, subject to the power balance constraint in Eq. (7). To enhance robustness against uncertainty, chance-constrained formulations such as Eq. (8) are frequently incorporated to ensure that key operational limits, represented by $g(x,\omega)$, including voltage bounds, current ratings, and SOC constraints, are satisfied with a user-defined reliability level, where ϵ denotes the acceptable probability of constraint violation.

$$Min_x C(x) + \mathbb{E}_{\omega\in\Omega}[Q(x,\omega)] \tag{5}$$

$$Q(x,\omega) = Min_{y_\omega} \sum_t (c_{dis}P_{dis}(t,\omega) + c_{ch}P_{ch}(t,\omega) + c_{ls}P_{ls}(t,\omega)) \tag{6}$$

$$P_{RE}(t,\omega) + P_{dis}(t,\omega) - P_{ch}(t,\omega) + P_{Aux}(t,\omega) \geq L(t,\omega) - L_{Shed}(t,\omega) \tag{7}$$

$$\Pr\{g(x,\omega) \leq 0\} \geq 1 - \epsilon \tag{8}$$

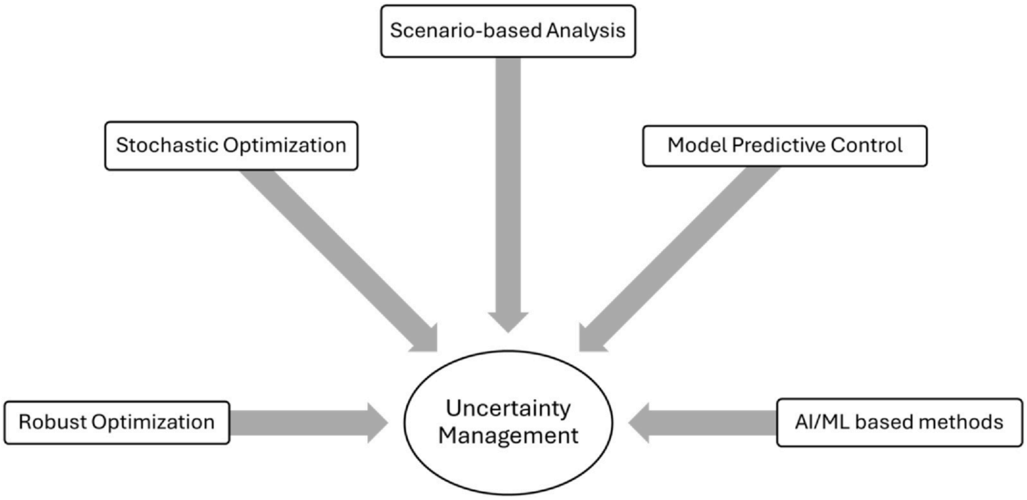


Fig. 12. Uncertainty management strategies for standalone DC microgrids. AI = artificial intelligence; DC = direct current; ML = machine learning.

Building on this foundation, several studies have advanced stochastic optimisation for standalone DC microgrids. Stochastic optimisation incorporating probability distributions for uncertain parameters has been widely adopted to improve operational robustness. For example, a multi-objective supervisory control model based on stochastic model predictive control (MPC) is developed in Mansoorhoseini et al. [211], where uncertainties in wind and solar resources and the influence of active and reactive power on system frequency are explicitly modelled. Simulation results demonstrate that the proposed MPC-based framework reduces operational cost and mitigates frequency and voltage deviations while reliably meeting active power demand and maintaining robustness through sensitivity analysis. Similarly, a 2-stage stochastic optimisation approach combined with a probabilistic PV forecasting model based on an ANN is presented in Abunima et al. [212]. By predicting PV output as a probability density function, the framework significantly reduces operational uncertainties, achieving high forecasting accuracy with normalised root mean squared error and mean absolute error values of 9.7% and 9.1%, respectively, and yielding improvements in cost minimisation and load-shedding reduction during islanded conditions.

Complementary developments in the literature highlight the increasing adoption of scenario-based stochastic optimisation approaches to co-optimise energy dispatch and flexibility provision in standalone DC microgrids. For instance, the scenario-driven framework in Antoniadou-Plytaria et al. [213] jointly minimises energy costs, peak power charges, and battery ageing while simultaneously maximising flexibility revenue. By incorporating multiple realistic scenarios, the method demonstrates effective flexibility dispatch and delivers measurable economic gains, achieving an operational cost reduction of at least 7%. In El Shamy et al. [214], a chance-constrained MILP formulation is introduced for optimal sizing of a microgrid integrating PV generation, hydrogen storage, and battery systems, guaranteeing a minimum of 80% reliability under uncertain solar irradiance and demand conditions.

Similarly, Najafi et al. [215] propose a Monte Carlo–based methodology that captures uncertainties in load and distributed generation, employing a modified PSO algorithm to optimise annual operational cost in a standalone DC microgrid. The results reveal faster convergence, improved optimisation performance, and an interpretable trade-off between LPSP and system cost. Collectively, these studies demonstrate the growing maturity and versatility of stochastic optimisation techniques in addressing uncertainty arising from renewable intermittency, load fluctuations, and flexibility pricing, ultimately enhancing economic efficiency, system reliability, and operational resilience in standalone DC microgrids.

7.2. Robust optimisation

In contrast to stochastic optimisation, which models uncertainty through probability distributions or scenario sets and seeks decisions that minimise expected cost, robust optimisation adopts a fundamentally different philosophy by ensuring feasibility and acceptable performance under *all* realisations of uncertainty within a prescribed uncertainty set [216]. Rather than relying on accurate probabilistic information, robust optimisation constructs solutions that remain valid under worst-case deviations in renewable generation, load demand, or component ageing, making it particularly attractive for standalone DC microgrids where data scarcity, extreme weather, and non-Gaussian disturbances are common [217].

Formally, a robust optimisation problem can be expressed as in Eq. (9), where x represents operational variables, $g(x, \omega)$ denotes system constraints under uncertainty, and $\mathscr{U}$ is an uncertainty set, which is represented in Eq. (10), defining all admissible variations in solar irradiance, load demand, or component parameters. A widely used structure in microgrid applications is the budget of uncertainty model is presented in Eq. (11), where $\bar{\omega}_i$ is the nominal value, δ_i defines the maximum deviation, and Γ adjusts the conservativeness of the optimisation. The robust counterpart of the deterministic linear constraint $Ax \le b(\omega)$ is then given by Eq. (12), ensuring feasibility against the most adverse ω within $\mathscr{U}$.

$$Min_x C(x) \quad s.\ t. \quad g(x, \omega) \le 0, \quad \forall\ \omega \epsilon \mathscr{U} \tag{9}$$

$$\mathscr{U} = \left\{ \omega\colon |\omega_i - \bar{\omega}_i|, \sum_{i=1}^{n} \frac{|\omega_i - \bar{\omega}_i|}{\delta_i} \le \Gamma \right\} \tag{10}$$

$$P_{RE}(t, \omega) + P_{dis}(t, \omega) - P_{ch}(t, \omega) + P_{Aux}(t, \omega) \ge L(t, \omega) - L_{Shed}(t, \omega) \tag{11}$$

$$\Pr\{g(x, \omega) \le 0\} \ge 1 - \epsilon \tag{12}$$

Several notable studies have addressed robust optimisation to enhance the reliability, stability, and economic efficiency of DC microgrids under uncertainty. In Yang and Su [218], a 2-stage robust optimisation model is proposed for microgrid operation, which balances economic efficiency and system robustness under uncertainty. Using the Benders dual algorithm and the complex linear programming expert solver, the approach demonstrates effectiveness in minimising operating costs while maintaining robustness across various electricity trading scenarios. A robust centralised state-feedback controller for standalone DC microgrids is proposed in Mehdi et al. [195], designed to handle parametric uncertainties in distributed generation units and reject external disturbances. Employing a linear time-varying model and Lyapunov-based stability analysis, the controller is developed by solving linear matrix inequality constraints to achieve sub-optimal gains while ensuring system stability. In Zheng et al. [219], an improved robust optimisation model is introduced, utilising interval-partitioned and temporally correlated uncertainty sets to reduce conservativeness and computational burden. This is achieved by decomposing the problem and integrating an outer approximation method within the column and constraint generation framework.

7.3. Scenario-based analysis

Scenario-generation techniques and metaheuristic optimisation methods form a complementary class of uncertainty management tools for standalone DC microgrids, particularly when analytical probability distributions or robust uncertainty sets are insufficient to capture the nonlinear, highly variable behaviour of RES and load patterns [220]. Scenario generation typically begins with statistical modelling of historical data using parametrised distributions such as beta or Weibull for solar irradiance and wind speed, followed by Monte Carlo sampling to produce a large ensemble of realisations representing possible future operating conditions. Because these raw scenario sets can be computationally prohibitive for optimisation, dimensionality reduction techniques, such as principal component analysis (PCA), K-means clustering, density-based clustering, or autoencoder neural networks, are applied to extract representative scenarios while preserving essential variability and correlation structure [221]. These reduced sets are then integrated into planning or operational models to evaluate dispatch feasibility, battery ageing behaviour, and RES curtailment under diverse uncertainty conditions.

Meta-heuristic methods, such as PSO, genetic algorithms, and hybrid evolutionary approaches, further enhance uncertainty handling by enabling global search over highly nonconvex design spaces [222]. For example, modified PSO formulations have been used to minimise annualised system cost while balancing the LPSP in standalone DC microgrids, offering faster convergence and improved performance relative to traditional deterministic optimisation [223]. Together, scenario-based modelling and heuristic search provide flexible, data-driven frameworks capable of capturing multi-dimensional uncertainty, identifying near-optimal configurations, and supporting robust microgrid design and operation without requiring restrictive assumptions about probability distributions or system linearity.

To address scenario generation and uncertainty, Gaddam et al. [224] propose statistical modelling of historical data using beta and Weibull distributions to extract key parameters, followed by Monte Carlo simulations to generate approximately 100 scenarios. To manage the complexity of analysing numerous scenarios, dimensionality reduction techniques such as PCA, K-means clustering, density-based spatial clustering, and autoencoders are used to retain essential features while reducing scenario volume. In [225], optimal scheduling for a stochastic reconfigurable DC microgrid is investigated, incorporating RES and dynamic line rating constraints to prevent line overloading via network reconfiguration. Using linearization and unscented transform techniques to address nonlinearities and uncertainties, the proposed method is validated on a modified IEEE-33 bus system, showing effective cost minimisation while satisfying all network constraints.

7.4. Model predictive control (MPC)

MPC offers a robust framework for managing uncertainty in standalone DC microgrids by explicitly forecasting future system behaviour and optimising control inputs over a receding time horizon. At each control step, MPC solves a constrained optimisation problem in which the predicted system states x_{t+k} evolve according to the dynamic model $x_{t+1} = f(x_t, u_t, w_t)$, where u_t represents control actions and w_t accounts for disturbances or forecast-dependent uncertainties. The standard MPC formulation seeks to minimise a quadratic or multi-objective cost function over the prediction horizon N, as expressed in Eq. (13), while satisfying operational constraints such as voltage limits, state-of-charge bounds, and converter ratings.

$$Min_{\{u_{t+k}\}_{k=0}^{N-1}} \sum_{k=0}^{N-1} \{\|x_{t+k} - x^{ref}\|_Q^2 + \|u_{t+k}\|_R^2\}, \quad x_{t+k} \in \mathscr{X}, u_{t+k} \in \mathscr{U}, \forall\ k = 0,\ \ldots, N-1 \tag{13}$$

Uncertainty enters the MPC formulation through forecast errors in renewable generation, load variations, and component ageing, which influence the disturbance term w_t. Stochastic MPC approaches address this by embedding probabilistic forecasts or disturbance distributions, enabling constraint satisfaction with specified confidence levels. In Wu et al. [226], a 2-layer MPC strategy is proposed to manage the charging of aggregated EVs in a microgrid, accounting for uncertainties in EV connection times and initial SOC through multi-uncertainty sampling; by integrating feedback from arriving EVs and considering extreme scenarios, the strategy enhances forecasting accuracy and improves charging-discharging regulation compared to conventional methods.

7.5. AI and ML-based methods

AI and ML techniques have emerged as powerful tools for managing uncertainty in standalone DC microgrids, particularly under variable renewable generation and stochastic load conditions. Methods such as deep learning, FL, and deep reinforcement learning (DRL) enable EMS to model complex, nonlinear dynamics and adaptively optimise control actions in uncertain environments [227]. Unlike conventional rule-based approaches, DRL treats EMS decisions as Markov decision processes, allowing control policies to be learned from historical data and refined through experience [228].

These AI-based approaches typically rely on high-resolution datasets, including PV generation and load measurements at 1–15-min intervals, to capture variability and improve prediction accuracy. A common workflow involves offline training of DRL agents, followed by online deployment for real-time microgrid control [229]. Bayesian DRL methods enhance robustness under high uncertainty by estimating probabilistic value functions, outperforming deterministic DRL approaches in stochastic conditions.

Applications of AI in standalone DC microgrids span several domains. Fuzzy logic and heuristic EMS have been implemented for desalination plants to optimise energy use and manage feed-in tariffs, demonstrating practical profitability and coordination among PV, diesel generators, and BESS [230]. PPO-based DRL has been applied for real-time EMS scheduling, effectively learning uncertainty patterns from historical data and enabling efficient online decision-making [231]. Bayesian DRL strategies further address challenges such as stochastic renewable generation, limited data on extreme events, and the need for fast, model-free control, improving policy stability and near-optimal performance under uncertainty [232].

Beyond real-time control, AI techniques also support day-ahead energy management planning. For instance, multi-objective EMS frameworks leverage probabilistic modelling, including Point Estimation Methods with correlated inputs via inverse Nataf transformation, and optimisation algorithms like the epsilon-constraint method to minimise operational costs and energy losses while satisfying technical constraints [233].

Overall, AI-driven methods enhance the resilience, adaptability, and efficiency of standalone DC microgrids by enabling advanced forecasting, probabilistic modelling, and adaptive control. By integrating these techniques into EMS architectures, microgrid operators can achieve robust uncertainty management, optimised energy utilisation, and reliable operation in remote or off-grid settings [234].

7.6. Comparison of different uncertainty management techniques

A comparative assessment of key uncertainty management strategies for standalone DC microgrids highlights their strengths, limitations, and suitable applications. Table 9 summarises these methods with horizons, target metrics, strengths, weaknesses, and applications, providing a benchmark-driven guide for selecting appropriate uncertainty management strategies.

Table 9 shows that uncertainty management strategies for standalone DC microgrids involve trade-offs between reliability, computational effort, and data requirements. Stochastic optimisation is cost-effective for short to medium term scheduling but relies on accurate probability distributions, while robust optimisation guarantees feasibility under worst case scenarios for critical systems, albeit with potential overdesign. Scenario-based analysis supports flexible long-term planning by evaluating multiple outcomes, whereas MPC enables real-time optimisation of multi-variable non-linear systems, dependent on model and forecast accuracy. AI/ML-based methods excel in highly non-linear, data-rich environments, learning optimal control policies from historical and real-time data, but require extensive high-quality datasets and validation.

8. Recommendations

The deployment of DC microgrids in standalone power systems presents considerable potential for reducing operational expenditure and GHG emissions compared with conventional diesel-based generation. Although notable progress has been made in energy management, voltage regulation, optimisation, and uncertainty handling, the systematic review reveals several areas that remain insufficiently explored. To provide a more actionable research agenda, future directions are prioritised based on their anticipated impact and technological feasibility, supported by corpus evidence from the reviewed literature. For each priority area, a minimal evaluation protocol is proposed to guide subsequent experimental and simulation studies.

8.1. High-impact near-term research priorities

High-impact, near-term priorities represent domains where immediate research effort can yield substantial improvements in standalone DC microgrid operation. One such domain is the integration of flexible loads, namely EV charging and on-site hydrogen production. Despite their relevance for rural and offshore applications, only a few

Table 9

Comparison of uncertainty management strategies for standalone DC microgrids

Strategy	Forecasting/control horizon	Target error/performance metrics	Strengths	Weaknesses	Applications
Stochastic Optimisation	Day ahead to week ahead	Cost deviation from demand, reliability metrics	Captures probabilistic uncertainties; cost-effective solutions	Requires accurate probability distributions; high computational burden	Long-term planning or operational scheduling
Robust Optimisation	Multi-day to months	Feasibility under worst-case scenarios	Ensures feasibility under uncertainty; does not require probability distributions	May overdesign; less cost-effective	Critical systems
Scenario-based Analysis	Long-term planning	Scenario coverage percentage	Captures a wide range of outcomes; flexible and intuitive	Tradeoff between comprehensiveness and computational complexity	Preliminary design phase
MPC	Minutes to hours	Weighted norm, cost function, deviation from setpoints	Handles multi-variable non-linear systems; predicts future states	Sensitive to model/forecast accuracy; high computational burden	Real-time decision making for non-linear systems
AI / ML-based methods	Seconds to hours	MAE, RMSE, MAPE	Handles non-linear and data-rich environments; improves with experience	Requires high-quality training data; black-box behaviour; extensive testing needed	Highly non-linear and data-dependent systems

AI = artificial intelligence; ML = machine learning; MPC = model predictive control.

reviewed studies (e.g. [235–237]) examined these loads within standalone DC microgrid optimisation frameworks. Their classification as non-critical loads enable load shifting, cost reduction, and opportunities for additional revenue streams. Future research should model systems incorporating RES, ESS, and hydrogen production, evaluating the benefits of flexible versus inflexible load operation using metrics such as operating cost, unmet demand, and DER utilisation.

Another near-term priority concerns the role of hierarchical control in improving microgrid performance. Although hierarchical control is discussed in several studies, only a few (e.g. [186,238]) evaluate its contribution to optimised standalone DC microgrid operation. Hierarchical control enables coordinated voltage regulation, power sharing, and cost optimisation, but its application to isolated systems remains limited. To advance this area, studies should assess a 3-layer control structure under variable demand and RES profiles, with performance metrics such as voltage deviation, convergence time, and communication overhead.

Integration of ancillary services, including black-start capability, reserve provision, and power-quality regulation, constitutes another high-impact, near-term research need. The review indicates that black-start capability is addressed in scarcely any studies (E.g. [239,240]), highlighting clear gaps in existing models. Given the critical importance of these ancillary services in isolated systems, future work should integrate them into EMS frameworks. Evaluation should be based on outage and restart scenarios, harmonic disturbances, and emergency operating conditions, using recovery time, reserve adequacy, and harmonic distortion as key performance indicators.

8.2. High-impact mid-term research priorities

High-impact, mid-term priorities focus on challenges that require further methodological development. One such challenge involves the computational burden associated with hierarchical and distributed control frameworks. Only a few studies (e.g. [241–243]) explicitly acknowledge the limitations imposed by hardware constraints, yet reducing computational complexity is essential for deployment in remote or resource-limited settings. Future work should examine reduced-order or computation-aware control algorithms deployed on low-power embedded systems, evaluating processor utilisation, execution time, control accuracy, and voltage stability.

Developing standardised benchmarking frameworks for uncertainty management also represents a high-impact, mid-term priority. Although several studies propose uncertainty-modelling techniques, only a few employ common datasets or comparative frameworks (e.g. [244,245]). Establishing standard benchmarks for resource, load, and weather uncertainty would enhance reproducibility and comparability across future studies. A suitable evaluation protocol includes multi-year datasets for renewable and load variability assessed using Monte Carlo analysis, stochastic programming, and robust optimisation, with performance evaluated based on expected cost, worst-case cost, and operational robustness.

8.3. Long term research priorities

Long-term research priorities include the development of scalable, modular microgrid architectures capable of accommodating evolving demand profiles and DER integration. Only a handful of reviewed studies (e.g. [246]) explicitly consider scalability, suggesting that this area remains underdeveloped. Modular architectures should be evaluated through scenarios that include system expansion, DER replacement, and topological reconfiguration, assessing interoperability, voltage stability, and reconfiguration time.

Resilience-oriented control strategies also represent a long-term requirement. Few studies (e.g. [247–249]) examine resilience mechanisms such as fault-tolerant control, sliding-mode observers, or cyber-resilient architectures. Considering the susceptibility of standalone systems to communication failures and cyber threats, future research should incorporate fault detection, isolation, and resilience mechanisms into microgrid control systems. Minimal evaluation protocols should include simulation of communication delays, cyberattack scenarios, and sensor failures, with metrics such as fault detection time, resilience indices, and post-disturbance stability [250].

Finally, several cross-cutting themes require continued attention. These include the development of accurate yet implementable system models, the integration of smart grid technologies to support monitoring and demand-side management, and the application of AI-enabled or data-driven approaches for forecasting and real-time optimisation [251]. Collectively, these targeted and prioritised research directions aim to enhance the reliability, adaptability, and long-term sustainability of standalone DC microgrids.

8.4. Emerging research directions in standalone DC microgrids

Emerging research on hybrid AC–DC microgrids reflects growing interest in combining the efficiency advantages of DC distribution with the widespread compatibility of AC networks. These hybrid architectures facilitate the integration of diverse energy sources, minimise conversion losses, and enhance operational flexibility, particularly in remote systems that must interface with legacy AC loads or onboard AC equipment [252]. Complementing this is the rapid rise of cybersecurity as a critical research priority. Increasing digitalisation, advanced communication links, and cloud-based supervisory systems expose microgrids to cyber threats that could compromise reliability and safety [253]. Current research focuses on intrusion detection systems, resilient control, encrypted communication, and anomaly-based monitoring tailored to the fast dynamics of DC networks.

Parallel efforts are visible in DSM and advanced protection mechanisms, both of which are essential for resilient standalone operation. DSM plays a crucial role in optimising energy utilisation by shifting, shedding, or prioritising loads to reduce peak demand and alleviate stress on storage systems, an especially valuable strategy for microgrids serving remote communities or industrial facilities [254]. At the same time, advanced protection solutions are being developed to address the unique challenges of DC faults, including high di/dt characteristics, lack of natural current zero-crossings, and strong coupling between sources. Adaptive protection schemes, fast fault isolation devices, improved fault-characterisation models, and coordinated protection strategies for hybrid AC–DC environments are key emerging themes [255]. Collectively, these areas are driving the next stage of innovation toward safer, smarter, and more reliable standalone DC microgrids.

9. Conclusion

Standalone DC microgrids represent a promising and sustainable alternative to conventional fossil fuel-based generation in remote and off-grid settings. Their advantages, including reduced conversion losses, efficient integration of RES, and compatibility with modern DC loads, make them an attractive solution for future decentralised energy systems. However, RES variability and the coordination of diverse subsystems continue to pose significant challenges across planning, operation, and uncertainty management.

Effective planning requires accurate characterisation of loads, renewable resource availability, and user requirements to ensure optimal sizing and configuration. While current optimisation-based methods support techno-economic decision making, their applicability remains constrained by simplified component models, limited availability of high-resolution field data, and insufficient treatment of emerging flexible loads such as EVs and hydrogen production. Addressing these gaps will improve the robustness and adaptability of planning frameworks. Reliable operation depends on well-designed control architectures and EMS. Although hierarchical and distributed control strategies have advanced significantly, EMS implementations still provide limited support for ancillary services such as black start, reserve management, and enhanced fault resilience. Further research is required to develop adaptive and self-healing EMS capable of maintaining stability under severe uncertainties and component failures.

Uncertainty management remains critical due to the stochastic behaviour of RES and remote-area loads. Probabilistic approaches, stochastic optimisation, and data-driven forecasting have improved decision-making; however, practical deployment is hindered by data scarcity, computational constraints, and the limited interpretability of AI/ML-based models. Future work should prioritise lightweight, explainable, and field-deployable uncertainty management tools. Although emerging technologies, such as advanced communication infrastructures and AI-enabled coordination, strengthen the potential of standalone DC microgrids, real-world validation remains limited. Large-scale demonstration projects and standardised performance benchmarks are needed to assess long-term reliability and economic feasibility.

This review synthesises current knowledge on planning, operation, and uncertainty management for standalone DC microgrids. While comprehensive, the study is constrained by the heterogeneity of existing research and the scarcity of field data. Addressing these limitations through coordinated research, standard development, and empirical validation will support the advancement and wider deployment of resilient and sustainable standalone DC microgrid solutions.

CRediT authorship contribution statement

Hasith Jayasinghe: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review and editing. **Kosala Gunawardane:** Conceptualization, Funding acquisition, Methodology, Project administration, Supervision, Writing – review and editing. **Md Alamgir Hossain:** Formal Analysis, Resources, Supervision, Validation, Visualization, Writing – review and editing. **Ramon Zamora:** Conceptualization, Funding acquisition, Project administration, Supervision, Writing – review and editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT and Gemini in order to improve language and readability. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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